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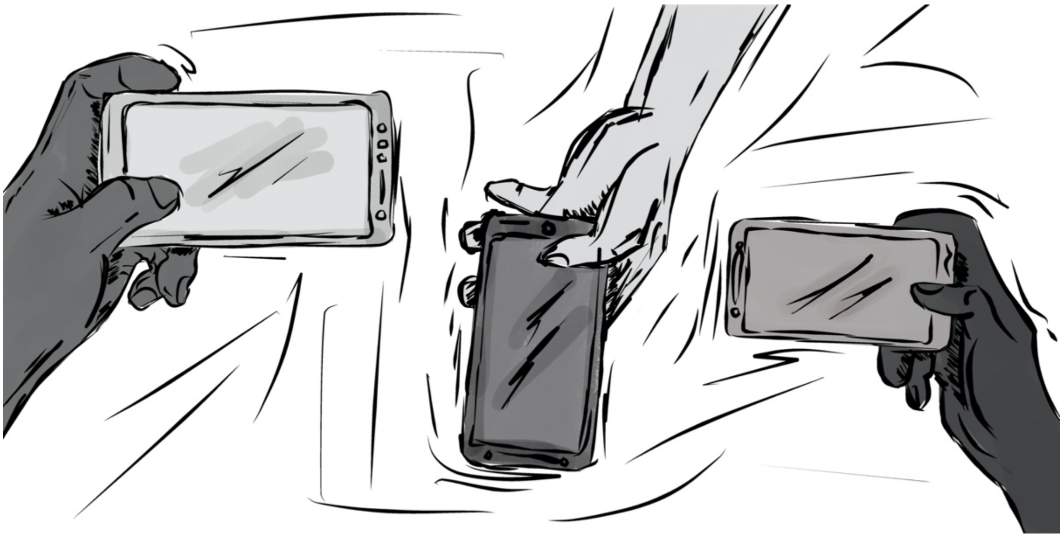
Examining individual differences through ‘everyday’ smartphone behaviours: Exploring theories and methods.



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Abstract

The mass adoption of digital technologies has instigated a transition whereby people are no longer 'independent organic actors' in society but have amalgamated with the technology they use on a daily basis. Consequently, people leave behind a 'digital fingerprint' whenever they use technologies such as smartphones, and the qualities of this trace can predict a variety of characteristics about the user. In this thesis, I explore how individual differences such as personality, demographics, and health relate to directly observable smartphone behaviours, that are logged 'in situ' via software installed on the device itself. By adopting an interdisciplinary approach between psychology and computer science, this thesis primarily considers the theoretical (chapter two), ethical (chapter three) and methodological (chapter four) underpinnings required to explore these human-smartphone relationships. Notably, traces of use do not have to be complex, as meta-data such as the smartphone operating system a person uses can reveal information regarding a user's personality, as long as there is trace-to-trait relevance. Findings from chapters five and six also reveal that some individual differences can be better predicted from objective smartphone use than others. For example, age and gender can be discerned from smartphone usage logs whereas, mental health variables only had small positive correlations with smartphone screen time. However, an important contribution of this thesis resides in its methodological considerations, as self-reports of technology use can impact the relationships with individual differences and cannot be used as a substitute for objective logs. All the above has applied implications for security and health, which can benefit from the ability to infer characteristics about people, when self-reports are arduous, unfeasible or lack scientific rigour.

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row illustrates how smartphone addiction scores, estimated and actual screen time correlate with mental health. Bottom row replaces estimated and actual screen time with pickups.

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Declarations

The content of this thesis is entirely the candidates own work, including all write up, data collection and analysis, carried out under normal terms of supervision. Consequently, there are differences between the thesis and published version of each chapter. This thesis was fully funded by the University of Lincoln, College of Social Science.

List of Publications

Chapter two

Shaw, H., Ellis, D. A., & Ziegler, F. V. (2018). The Technology Integration Model (TIM). Predicting the continued use of technology. *Computers in Human Behavior*, *83,* 204-214. https://doi.org/10.1016/j.chb.2018.02.001

Chapter three

Shaw, H., Ellis, D. A., Kendrick, L.-R., Ziegler, F., & Wiseman, R. (2016). Predicting Smartphone Operating System from Personality and Individual Differences. *Cyberpsychology, Behavior, and Social Networking*, *19*, 727-732. https://doi.org/10.1089/cyber.2016.0324

Chapter four

Andrews, S., Ellis, D. A., Shaw, H., & Piwek, L. (2015). Beyond Self-Report: Tools to Compare Estimated and Real-World Smartphone Use. *Plos One*, *10*, e0139004. https://doi.org/10.1371/journal.pone.0139004

Ellis, D. A., Davidson, B. I., Shaw, H., & Geyer, K. (2019). Do smartphone usage scales predict behavior? *International Journal of Human Computer Studies*, *130*, 86–92. https://doi.org/10.1016/j.ijhcs.2019.05.004

Wilcockson, T. D. W., Ellis, D. A., & Shaw, H. (2018). Determining Typical Smartphone Usage: What Data Do We Need? *Cyberpsychology, Behavior, and Social Networking*, *21*, 395–398. https://doi.org/10.1089/cyber.2017.0652

Chapter six

Shaw, H., Ellis, D. A., Geyer, K., Davidson, B. I., Ziegler, F. V., & Smith, A. (2020). Quantifying Smartphone "Use": Choice of Measurement Impacts Relationships Between "Usage" and Health. *Technology, Mind, and Behavior, 1, 1-15.* https://doi.org/10.1037/tmb0000022

Chapter 1

Introduction

1.1. A Society of Digital Traces

1.1.1. The Digital Revolution

From the abacus to the iPhone, many technological developments have ultimately led to digital computers permeating nearly every aspect of our existence (Heath & Best, 2011). In the workplace, we use email, Google Docs and Skype to aid collaborations and task efficiency (Widdicks, Ringenson, Pargman, Kuppusamy, & Lago, 2018). At home, podcasts, on demand video content, social media sites and instant messaging services entertain us and facilitate social interaction (Widdicks et al., 2018). Furthermore, mass communication allows for the long-distance travel of social information, mediated through different forms of technology (Chandler & Munday, 2016). Thus, people are becoming part of an information network, fuelled by the ever-growing number of devices connecting to the 'internet of things', that communicate not only with the user, but with other devices autonomously (Yury, 2017). This mass adoption of electronic hardware has instigated a transition whereby people are no longer 'independent organic actors' in society but have amalgamated with the technology they use on a daily basis. With the further increase of wearable technologies and digital implants becoming available on the consumer market (Pelegrín-Borondo, Reinares-Lara, & Olarte-Pascual, 2017; Piwek, et al, 2016), it is no surprise that some scholars are claiming that digital technology is now extending what it means to be human (Belk, 2013).

Notably, at the beginning of the 20^{th} century, communication technology as we know it did not exist. Only 10% of US households had a landline telephone in 1903, and many did not have electric power, automobiles, vacuum cleaners, radios, refrigerators or washing machines (Desjardins, 2018). In contrast, by 2008, the number of objects connected to the internet exceeded the number of people on earth (Swan, 2012). Coined the 'digital revolution', this rise in information technology means our search for knowledge, culture, social interactions, and material goods largely exist in digital form (Hodson, 2018). Consequently, wherever we go, people leave behind a digital trace, which is indicative of their previous actions. This 'digital footprint' may consist of every movement, every transaction, and every record (e.g., a documented Facebook 'like') a person makes (Weaver & Gahegan, 2007). Whilst this may have started with CCTV and telecommunication records, a search through an individuals' 'Google activity' may contain a historical account of their behaviour, such as, the videos a person has watched on YouTube, audio clips of a user's voice when using Google Assistant, and the locations visited using Google Maps (Google, 2020). This rich and longitudinal account of people's behaviour has consequently, been used by many companies to build up a 'consumer profile' of a person's characteristics based on the way they have been using technology (Krämer, Schnurr, & Wohlfarth, 2019; Lies, 2019; Weaver & Gahegan, 2007). Corporations such as, Facebook and Amazon have capitalised on this information for digital marketing, which includes targeted advertising, automated price adjustments and product recommendations (Krämer et al., 2019; Lies, 2019).

It can be argued that such companies are more informed of current human behaviours, characteristics, and demographics than many psychologists and social scientists. For example, it has been demonstrated that a collection of Facebook ‘likes’ can be used to predict a range of highly sensitive attributes such as a person’s sexual orientation, ethnicity, religious and political views, personality traits, intelligence, happiness, use of addictive substances, parental separation, age, and gender (Kosinski, Stillwell, & Graepel, 2013). However, within academia, the emergence of digital traces provides endless research opportunities across many disciplines to study numerous aspects of modern life. For the first time in history, we can study in real-time the effects of a major societal change, such as the ‘digital revolution’, or the advent of smartphones on the collective human experience, by directly monitoring user engagement and the consequence of such activities. It is also possible to ascertain why people use technology in the first place, and whether human-technology interactions are intrinsic to human nature. We can start to learn how human behaviours are extended or mediated through the use of technology, such as social interactions or criminal behaviour. Finally, it is possible to explore how a person’s technology use is related to psychological phenomena, such as habit formation, personality, self-identity, stereotypes, mental health, and cognitions. As part of this, one may explore how a person’s mobile technology use can be indicative of a person’s individual differences, a prevalent research question in the following chapters of this thesis. Therefore, by studying digital traces of behaviour in psychological research, it is possible to generate endless new streams of research, such as those described above.

1.1.2. Mobile Technologies

In the age of ubiquitous computing *"the most profound technologies are those that disappear. They weave themselves into the fabric of everyday life until they are indistinguishable from it."* (Weiser, 1991, p. 24). One particular technology that has truly embedded itself into the operations of everyday living is the smartphone, an 'all-in-one' device whereby individual applications are analogous to individual tools within a Swiss army knife. In 1994, IBM distributed the Simon Personal Communicator, which combined a cell phone with a touchscreen, and many applications including an address book, calendar, calculator, clock, and an electronic notepad, with the potential of additional features such as maps, GPS, and stocks (IBM, 1994). However, the Simon did not reach commercial success due to its expense, and bulky design (Merchant, 2017). Over a decade later, on January the 9th 2007, Steve Jobs unveiled the first ever iPhone, which combined the iPod, mobile phone, and internet communication into one device (Merchant, 2017). Remarkably, by 2016, the iPhone was the best-selling computer of all time (Merchant, 2017).

In accordance, countries such as the U.K. have been labelled a 'smartphone society' (OFCOM, 2015). Across the Atlantic, 81% of Americans in 2019 owned a smartphone in comparison to just 35% in 2011 (PEW, 2019). The rise in popularity of these hand-held computer/phone hybrids can be attributed to their ability to bring together several functions that, prior to the invention of smartphones, would have been carried out using separate technologies. People are motivated to use smartphones for several reasons, including the management of schedules, bank accounts, keep up with world affairs, shop, listen to music, communicate, follow fashion trends, and navigate unknown areas (Kim & Lee, 2018). Their use is further motivated by the fact they can be used anywhere, independent of time and place, and their portability allows them to be at constant disposal to the user (Kim & Lee, 2018). Consequently, smartphones are used on average between 3.74 and 4.62 hours each day (see chapters four, five and six) and people consider their smartphone to be the most important device for connecting to the internet, even when compared to laptops, tablets, and desktop computers (OFCOM, 2018). Hence, some posit that smartphone use is now simply part of our way of life (Thompson & Thompson, 2017).

Subsequently, smartphones are an invaluable resource when analysing digital traces of behaviour as the use of smartphones and their applications alone capture an unprecedented amount of digital activities. For example, by examining social behaviours through a collection of smartphone traces such as call logs, message logs, and social media hits, alongside conversations sensed through the microphone, it is possible to retrieve a comprehensive account of a person's social behaviours (Harari et al., 2019). Furthermore, Bluetooth sensors can be used to infer the social context a person resides in, such as weekly group meetings or lunch with family members by assessing the proximity and number of people in a given environment (Do & Gatica-Perez, 2011). The time people spend on their smartphones can be measured objectively through logging applications and have the ability to document a person's routine and chronotype (whether they are a 'morning' or 'evening' person) (Aledavood, Lehmann, & Saramäki, 2018; Aledavood et al., 2015). Thus, smartphones alone can capture unapparelled amounts of contextual and behavioural data.

As a result, digital traces can be used to answer theoretical questions in psychology. Examples of this include logging smartphone usage to ascertain if personality traits relate to the use of social applications such as WhatsApp (Montag, et al. 2015b). Others have used GPS tracking to address questions regarding physical segregation and prejudice towards specific groups (Dixon et al. 2020). Furthermore, the ability to detect and monitor changes in mental health symptomology via smartphone sensors allows for better understanding of longitudinal patterns within these disorders (Cornet & Holden, 2018). Thus, due to their mass adoption, continuous close proximity to the user, and general immersion in many aspects of people's lives, smartphones have large potential when it comes to measuring digital traces of behaviour. Consequently, this thesis is interested in examining the behaviours and psychological aspects of the user that can be captured and retrieved through the use of mobile technologies. This outlines the first objective of this thesis; a methodological exploration of digital behaviours that can be captured through smartphones and goes beyond traditional self-report methods of technology use.

1.2. Responses to the Rise of Communication Technologies in Social Science Disciplines.

1.2.1. Methodologies in existing studies

Optimism about the mass uptake of communication technology is not universally shared, as whenever a new technology is widely adopted, there is a pattern of research priorities which largely study the assumed or expected negative consequences of its use (Davidson et al., 2019). Historically, concerns regarding mass communication technology has been studied with a variety of different methodological approaches. In social psychology, laboratory experiments have shown that a likeable communicator (e.g., a charismatic dictator) is more persuasive if sending a message via videotaped or audiotaped technology than written (Chaiken & Eagly, 1983). In sociology, many adopt an observational approach for example, pairing societal changes such as the mass consumption of motion pictures with changes in what is deemed 'acceptable' behaviours (Weinbrenner, 2011). Others have conducted cross sectional and survey-based research to demonstrate how time spent in technology (e.g., watching television) may have a negative impact on health and cognitive skills such as reading (Neuman, 1988). However, for the first time in history, it is now possible to study the digital traces of these behaviours to objectively and longitudinally understand how the use of these mass communication technologies impacts wider society. It can be further considered, that if these approaches were possible during the advent of technologies such as television, radio, newspapers, magazines, and films, that we may have understood and interpreted their societal effects in a radically different manner.

1.2.2. Problematic smartphone use

Notably, there is a wealth of articles advocating that excessive smartphone use is a public health concern (Kwon et al., 2013; Lee et al., 2016; Long et al., 2016; van Velthoven, Powell, & Powell, 2018). Consequently, within psychology disciplines, smartphones have predominantly been studied in the context of assessing concerns about their use. These include issues regarding daily screen time (Lissak, 2018), social media use (Satchell et al., 2019), nomophobia (the fear of being out of mobile contact) (Yildirim & Correia, 2015), and a phenomena called 'phubbing' which is being snubbed by someone using their smartphone (Roberts & David, 2016). Specifically, existing literature suggests that increased smartphone use is linked to ocular symptoms, sedentary behaviour, lower cardiorespiratory health, lower sleep quality, depression, anxiety, stress, and reduced muscle mass (Exelmans & Van-den-Bulck, 2016; Kim et al., 2016; Kim, Kim, & Jee, 2015; Lepp, et al., 2013; Thomée, 2018). However, understanding the genuine impact smartphones have on individuals and society has wide implications for healthcare practitioners, policy, and engineering. It is important to note that in contrast to the above, that the use of smartphones is considered an important part of the digital health revolution (Chandrashekar, 2018; Anthes, 2016). By examining digital traces of smartphone use, findings from studies which examine the wellbeing effects of usage become closer to ground truth due to heightened construct-validity (see chapter 4 and 6). This change in methodology is urgently needed because the lack of quality in existing research makes it problematic for governments to implement specific guidelines (Science and Technology Commitee, 2019). Consequently, this thesis explores whether measuring digital traces of smartphone use can enhance or alter our understanding of health and technology use relationships (see chapter six).

1.2.3. The Addiction Narrative

A predominant research field in psychology is the study of smartphone addiction. Notably, measuring smartphone use via digital traces is completely devoid from smartphone addiction research, so researchers are unable to ascertain whether actual, rather than self-reported use is related to negative health consequences (Boase & Ling, 2013; Ellis, 2019). This is particularly problematic given that smartphone addiction is posited to be a public health concern in regard to people's mental well-being (Kwon et al., 2013; Thomée, 2018). Notably, concerns regarding overuse have led to a wealth of usage scales being created to measure constructs including 'addiction', 'nomophobia' and 'problematic use' (Ellis, 2019; Thomée, 2018). Despite having 'use' in their name, it is yet to be studied whether these measures can actually be used as a substitute for behavioural measures of smartphone use. In light of this, chapter four explores the validity of using psychometric scales and temporal estimates as a proxy for smartphone usage.

It is somewhat ironic that the 'behavioural' addiction approach, which incorporates the study of smartphone addiction is lacking the study of actual behaviour. Yet many elements of the behavioural addiction approach could be adequately assessed using digital traces of behaviour. Specifically, all addictions which do not involve ingesting a substance are said to have the same underlying components: salience, mood modification, tolerance, withdrawal effects, conflict, and relapse (Griffiths, 2005). Thus, if someone undergoes a smartphone abstinence, potential relapse effects could be assessed by examining the logs of smartphone use immediately after the abstinence period. Additionally, tolerance could be measured by seeing whether people's objective smartphone use gradually increases over time. Chapter four in particular evaluates the idea of smartphone tolerance through studying whether increased objective smartphone use is related to smartphone addiction measures.

However, beyond measurement issues, the addiction framework has faced many criticisms when it comes to conceptualising problematic technology use. The notion of tolerance in technology addictions have been critiqued, as research has shown that people with self-reported internet gaming disorder did not feel the need to increase their time spent gaming (King, Herd, & Delfabbro, 2017). Others state that behavioural addictions borrowed terms such as 'tolerance' or 'withdrawal' to legitimise their existence, and do not apply to non-substance ingesting behaviours (Starcevic, 2016). This is symptomatic of the main issue underlying the addiction framework. There is no consensus on how to define, measure or treat those with problematic use (Mihajlov & Vejmelka, 2017). This is likely because findings change dependent on the authors objectification of addiction and its components (see chapter six; Kaptsis, King, Delfabbro, & Gradisar, 2016). Consequently, this lack of consensus makes it difficult to provide policy suggestions, which require clear and implementable solutions.

1.2.4. Everyday smartphone behaviours

Moving forward, it can be argued that first we should understand and objectively log what the 'norms' of smartphone use consists of through the use of digital traces. This would advocate abandoning the notional of pathologizing smartphone behaviours due to the basis that little is currently known about normative behaviours. Only that way can researchers truly understand what abnormal use would consist of by studying how these individuals might deviate from this 'norm'. Theories predicting everyday smartphone usage behaviours however are largely absent from the psychological literature, making it difficult to establish a starting point regarding predictions. As a consequence, chapter two explores theories of 'everyday' technology use to establish a strong theoretical basis for future research. Accordingly, whilst some may think that using a smartphone for several hours a day may be problematic, this could actually be the standard when assessing longitudinal usage logs of behaviour (see chapters four, five and six). However, researchers could only genuinely establish this by looking at people's daily smartphone usage logs on a longitudinal basis, and through examining the particular applications people often engage with. This outlines the second objective of this thesis; an exploration of 'everyday' smartphone uses that challenges and goes beyond existing narratives portrayed in psychology research.

1.3. Decline of Behaviour and Rise of Self-Reports in Psychology

1.3.1. Cognition vs Behaviour

The lack of behavioural measurement when assessing technology use aligns with a general trend in social psychology, whereby since the 1980's, there has been a steady decrease in the number of studies which measure behaviour (Baumeister, Vohs, & Funder, 2007). In part, this could be due to the rise of the cognitive revolution which heavily critiqued the radical behaviourist approach and its denial of mental processes (Leahey, 2013). Whilst the cognitive revolution addressed this issue this by recognising the mental causation of behaviour, over time, researchers have become so focused on cognitive processes that their explorations have become devoid of linking these to actual behaviour all together (Baumeister, Vohs, & Funder, 2007). This puts psychology at risk of only understanding inner states, which takes the discipline back to the study of introspection and self-reports, not unlike Wundtian psychology (Kendler, 1987). With relevance to smartphone use, by only studying exclusively smartphones behaviour or alternatively our experience with smartphones, researchers are actually missing half the picture. Digital traces allow for the direct measurement of technology usage behaviours, which can be complimented through self-reports of people's affective states (see chapter six).

One of the main issues with introspection is that an individual is not always privy to the cognitive processes that lead to their own behaviour (Nisbett & Wilson, 1977). This may be one reason why self-reports do not always align with behaviour (Cyders & Coskunpinar, 2011; Prince et al., 2008; West & Brown, 1975). For example, when asking those to donate money during an emergency situation, the average amount of money people claim they would donate in a laboratory environment was much higher than what people actually donated in real-life simulations (West & Brown, 1975). Likewise, when making direct comparisons between the two methods, small effect sizes have been found between self-reports of impulsivity (e.g., personality trait assessments of impulsivity) and laboratory based behavioural assessments (Cyders & Coskunpinar, 2011). Furthermore, a recent systematic review of 148 studies comparing self-reports of exercise (e.g., questionnaire, diary) to behavioural measures (e.g., accelerometery, double labelled water) showed a mean correlation of 0.37 between the two (medium effect) (Prince et al., 2008). Chapter four of this thesis provides further evidence that self-reports of smartphone use do not correlate highly with actual smartphone behaviours. Therefore, psychologists should use self-reports to help aid our understanding of human behaviour, rather than entirely supersede any study of behaviour. The same can be said regarding our understanding of technology and smartphone use, which requires both an assessment of behaviours and the cognitive processes behind its use (see chapter two).

1.3.2. Absence of behaviour in Social Psychology

When assessing the size of this issue, it is possible to consult articles which review the prevalence of self-reports in psychology journals. Examination of a 2006 issue of the Journal of Personality and Social Psychology, showed that all apart from one study (which involved decision making), were absent of any direct observations of behaviour (n = 38) (Baumeister, Vohs, & Funder, 2007). Ten years later, the same journal was examined (volume 113 in 2017). Out of the 290 studies, only 6% of articles (n = 18) studied any sort of behaviour (Doliński, 2018). When both articles further investigated the types of behaviours being measured, they were far from the historical methods in psychology, which examined people's behaviours in vivid contexts (e.g., Milgram, 1963), but often involved people's "finger movements" and button pressing in response to computational tasks (Baumeister, Vohs, & Funder, 2007; Doliński, 2018).

One might ask if this is really the behaviour of interest to many psychologists? Are we as a discipline solely interested in predicting what leads to people pressing buttons on a keyboard? Or instead are we interested in how people use technology to start political movements, share content and promote new ideas, or less joyous aspects of technology use such as online trolling. As put powerfully by Baumeister, Vohs, and Funder, (2007, pp. 399), *"whatever happened to helping, hurting, playing, working, taking, eating, risking, waiting, flirting, goofing off, showing off, giving up, screwing up…"*. Likewise, by studying people's digital footprints, it is possible to measure peoples 'searching', 'texting', 'liking', 'binge watching', 'vlogging' and 'posting' behaviours. Of particular relevance to chapter five, it is possible to directly explore the rich and unique temporal patterns in people's daily screen time and application usage behaviours which form their distinctive 'smartphone personality'.

1.3.3. Absence of behaviour in Cyberpsychology

This trend in increased self-report measures has also been found in the study of technology use and cyberpsychology (Howard & Jayne, 2015). A review of 1400 articles, 900 scales and 17 years of research highlighted that often authors are forced to administer self-made psychometrics scales due to the rapid change in technologies, which have little or no investigation as to their psychometric properties or validity (Howard & Jayne, 2015). Likewise, there has been a rise of self-report scales being made to assess different aspects of smartphone use, with the same criticisms regarding their development (Ellis, 2019). However, the study of technology use is in a privileged position, given that the technology itself often has the ability to produce logs which can document exactly how it was used (Piwek, Ellis, & Andrews, 2016). Researchers should take advantage of this possibility and enhance research methods by logging behaviour through 'social sensing' technology, instead of having a narrow focus of solely exploring the potential harms of technology use. By doing so, psychology can once again become the study of human behaviour through taking advantage of recent technological developments.

1.4. The Intersect of Psychology and Computer Science

1.4.1. New disciplines

There is promise in new endeavours which seek to utilise the vast and ever-increasing universe of digital data. In 2013, there were 4.4. trillion gigabytes of data world-wide, with a projection that this would double in size every two years (International Data Corporation, 2014). This would predict a digital universe equating to 44 trillion gigabytes in 2020. Consequently, several psychology labs across the globe including our own (see psychsensorlab.com) are starting to explore this new influx of digital data, in new fields such as *"Archival Research"* (Heng, et al., 2018), *"Psychoinformatics"* (Yarkoni, 2012), *"Computational Social Science"* (Lazer et al., 2009) and *"Behavioural Analytics"* (CREST, 2020). Despite the different names, each of these fields have the same goal of exploring 'big data' on digital platforms, using computer science methodologies and analysis techniques, to answer social science questions. This thesis, therefore, adopts an interdisciplinary perspective, combining both computer science and psychological methodologies to answer key questions regarding how technology use relates to personality, demographics, and health. This relates back to the first objective of this thesis which involves exploring the utility of new methods, such as smartphone behavioural tracking, as an alternative to self-report methods.

This combining of methodologies was first discussed when Lazer et al., (2009) published their seminal paper *"Computational Social Science"* discussing how telecommunication companies and websites such as Yahoo and Google can assess societal level communication patterns through call and instant messenger data. Since then, sub-disciplines such as *'Psychoinformatics'* show that data from human-machine interaction (e.g., Facebook and Twitter) can be used to successfully predict psychological variables (Montag, Duke, & Markowetz, 2016). For example, a study of over 509 million tweets showed that language use on twitter can be used to assess world-wide temporal trends in positive and negative affect (Golder & Macy, 2011). Furthermore, 'orderliness' has been shown to positively correlate with academic performance but was measured through the regularity of purchase records of showers and meals obtained from 18,960 student smartcards on a university campus (Cao et al., 2018). Moreover, text analysis of Facebook posts from 201 adults has shown that individuals with higher depression and anxiety expressed negative emotions more frequently on Facebook (Settanni & Marengo, 2015). Importantly, none of this work requires new technological inventions, but solely involves utilising cross-discipline collaborations and applying standard computer science techniques to psychological problems (Yarkoni, 2012).

1.4.2. Smartphone Methodologies

Smartphones play an important part in the acquisition of this digital data. In 2011, a paper titled *"Social fMRI: Investigating and shaping social mechanisms in the real world"* highlighted the potential of smartphone data collection in social science disciplines by installing a custom-built application on the smartphones of 130 participants (64 families) (Aharony, Pan, Ip, Khayal, & Pentland, 2011). Using the fMRI analogy, they documented and imaged social systems by inferring face to face interactions from Bluetooth scans of other devices in range. They discovered that people who spend more time in face-to-face interactions with each other were more likely to share common applications, documenting how ideas and information might spread during exchanges (Aharony et al., 2011).

In addition to Bluetooth sensors, smartphones have a wealth of sensors such as WIFI, GPS, NFC, cellular network, digital camera, light sensors, accelerometer, phone status logs, applications usage logs, SMS logs and call logs which can all measure varying aspects of human behaviour (Piwek & Joinson, 2017). Measuring digital traces from even one of these sensors can provide longitude and second-by-second behavioural monitoring. Therefore, a combination of smartphone sensors has massive potential for documenting a rich account of the human condition. These are now being made accessible to researchers through the development of programming frameworks which facilitate the process of creating applications for research purposes (Piwek, Ellis, & Andrews, 2016). Chapter four in particular explores the utility of programming frameworks and inbuilt logging systems when measuring digital traces of smartphone use. Consequently, in a paper discussing the *"Smartphone Psychology Manifesto"* it has been argued that *"smartphones could transform psychology even more profoundly than PC's and brain imaging did"* (Miller, 2012, pp. 221).

These smartphone sensors can be incorporated into sophisticated 'psych apps' which could include consent forms, interactive surveys, experiments, debriefs (Miller, 2012). Recruitment could be large scale and world-wide through making the applications available on app stores. Data collection can occur 'in situ' in real-word contexts without the temporal limits of designated laboratory sessions. In fact, smartphones can become 'pocket labs' due to their exceptional computational power and their ability to run cognitive and perceptual experiments with millisecond timing, making them superior to standard internet studies (Dufau et al., 2011). Smartphones can even be extended by linking them to wearable technology, such as mobile EEG sensors creating never endless potential for psychological research (Stopczynski, et al., 2014). Moreover, they can also act a central hub for ambulatory assessment, which collects momentary self-report, observational or physiological methods in real-time (Trull & Ebner-Priemer, 2014). For example, questions can be sent to the user's smartphone in ecological settings, when the device has sensed a person is in a specific context. As Miller, (2012) describes, if psychology had no history and was becoming a discipline for the first time today, these unobtrusive, sensor rich, computationally powerful, ubiquitous, remotely accessible, and omnipresent devices would be a psychologist's data collection tool of choice.

1.4.4. Academic Applications of Smartphone Methodologies

The use of smartphones in psychological research has developed during a time when psychology has undergone several 'crisis' whereby scholars have questioned their faith in its research practices. Issues include the replication crisis (Open Science Collaboration, 2015), underpowered studies (Button et al., 2013), measurement crisis (Flake & Fried, 2019), p-hacking (Simmons, Nelson, & Simonsohn, 2011), publication bias (Ferguson & Heene, 2012), and the theory crisis (Oberauer & Lewandowsky, 2019). Accordingly, a replication attempt of 21 social science studies published in Nature and Science between 2010 and 2015 showed effect sizes were on average 50% less than the original effect (Camerer et al., 2018). Thus, psychology, like all disciplines, has challenges and limitations regarding the generalisability of conclusions and research design. However, it is possible to aid some of these issues through procedural changes that are now possible through the use of smartphone methodologies.

This can be illustrated by evaluating a particular project which explored how the use of search engines can influence our memory abilities for information available online. In the original study, findings across several laboratory experiments indicated that people forget information which they can access externally (e.g., via Google) and remember items they think are not available (Sparrow, Liu, & Wegner, 2011). However, some of their findings failed to replicate (Camerer et al., 2018). It can be said that this replication may have failed because the original authors did not provide materials or provide any feedback on enquiries to aid the replication attempt at initiation (Camerer et al., 2018). This lack of open materials is one of the biggest issues facing psychology and has been advocated as one of the solutions to the replication crisis (Munafò et al., 2017). However, the replication may have failed due to other validity and reliability issues.

By using a Psychoinformatics approach, some of these concerns could be addressed. To elaborate, the research question could be operationalised using a 'psych app', whereby participants are presented with nonsensical facts and are told they could 'bank' 50% of them, with the belief that these could be accessed during the recall phase. Recall could be assessed after a designated time period, but in comparison to the lab, would involve the participant continuing with their everyday activities between training and recall, resulting in greater ecological validity. The interval between training and recall is not confined to a particular lab session, so could occur hours or days apart, being more realistic to everyday recall tasks. This ‘psych app’ could then be placed on the app store as a memory game, with a potential world-wide subject pool. The code for the application could be made open source on sites like Git-hub, so others could directly use it or modify it for their own research purposes. Further research questions could be assessed including whether learning or recall is better across certain days of the week or when in specific contexts.

Consequently, the heightened ecological validity, heightened power (as a result of greater sample sizes), readily available study materials and the ability to conduct longitudinal designs could put the Psychoinformatics approach in a promising position when addressing the replication crisis, the measurement crisis, and beyond. With the addition of open source data, it would be easier for others to conduct meta-analysis. Furthermore, with the assessment of actual behaviours in varying contexts, theories could holistically explain out-of-the-lab behaviours. Therefore, using smartphone methodologies during data collection could have wide scientific impact and academic value when pursuing psychological research endeavours.

1.4.5. Health Applications

The applied value of assessing individual differences using smartphone data collection methods spans widely, promising benefits to healthcare settings. Consequently, platforms such as Apple’s ResearchKit and CareKit allow for the development of medical and health-care research applications (Apple, 2020). This has included the ‘Autism & Beyond’ application, which uses the front facing camera on the iPhone to recognise facial emotions in response to videos in children as young as 18 months to help aid early autism diagnosis ("Autism & Beyond," 2014). Likewise, the 'Concussion Tracker' application monitors heart rate patterns and records physical and cognitive functions for six weeks after a concussion to monitor recovery (NYU Langone Health, 2020). Notably, these are just two examples of a wide array of mobile health or 'm-health' technology that is being developed with the purpose of aiding wellbeing with relevance to psychological research (Chandrashekar, 2018).

In accordance, a 2015 World Health Organisation (WHO) survey of 15,000 'm-health' applications showed 29% of them were involved in the treatment/diagnosis/support of mental health issues (Anthes, 2016). However, it is possible that the use of smartphone themselves, documented through logging applications, have predictive qualities when concerning a person's mental well-being. As mentioned previously, by adopting a Psychoinformatics approach, smartphone applications can be used to properly assess smartphone addictions (Montag et al., 2015a) as well as other technology addictions (Ellis, Kaye, Wilcockson, & Ryding, 2018). Others have developed a smartphone application called 'MoodScope' which could infer the mood of its operator based on how the smartphone is used after two months of training (Likamwa, et al., 2013). Chapter six of this thesis further explores whether technology usage patterns can predict scores on clinically validated anxiety and depression measures. Thus 'psych apps' have wide applied value as the U.K. National Health Service (NHS) and the U.S. Institute of Mental Health (NIMH) have used mental health applications as a cost effective and wide-reaching solution to the mental health treatment gap (Chandrashekar, 2018). Finally, by exploring whether 'everyday' smartphone use is inherently pathological via documenting digital traces of behaviours, it is possible to address the second of objective of this thesis and explore alternative narratives when depicting the relationships people have with their smartphones.

1.4.6. Security Applications

Smartphone applications alongside the analysis of digital traces of behaviour can also have an applied role in security settings. For example, biometric recognition of people's faces, voices, and fingerprints are now possible through smartphone sensing and can be used to remotely authenticate purchases or approve the access of sensitive information (Blanco-Gonzalo, et al., 2018). Through the use of experience sampling and GPS tracking, researchers can assess the contextual factors which lead to people perceiving certain areas as more crime-prone using crowd-sourcing applications (Solymosi, et al., 2019). Others have explored how smartphone accelerometer sensors could detect assaults in real-time by detecting distinct movement patterns (Sun et al., 2017). Of specific importance to this thesis, it has been shown that the set of applications a user has installed is very unique to the individual, and application usage traces could act as a 'digital fingerprint' when identifying users from a crowd (Tu et al., 2018). Consequently, a person of interest could be identified across devices (i.e. personal vs. 'burner' phone), or if usage patterns deviate from a person's norm, this may flag a potential hack or insider attack. Chapters three and five extend this idea by investigating whether a person's smartphone operating system of choice and usage patterns could be used to psychological profile an individual's characteristics. Therefore, beyond commercial and advertising purposes, the use of smartphone technology could create a safer society due to these security applications. This outlines a third objective of this thesis, which seeks to ascertain if digital traces of smartphone behaviour can predict individual differences such as personality, demographics, and health.

1.5. The Study of Individual Differences

1.5.1. Computer Science Methods and Individual Differences

Specific to this thesis, the Psychoinformatics approach can be used to further our understanding of individual differences, including the role they play in technology acquisition (see chapter three) and technology usage patterns (see chapter's five and six). Individual differences refer to the similarities and differences in how people think, feel, and behave and tends to focus on stable rather than transitionary characteristics that a person may possess (Maltby, Day, & Macaskill, 2010). However, there is a general acknowledgement that people can change over time through learning new skills and other life experiences (Sackett, et al., 2017). Through using computer science methods, it is possible to directly and longitudinally measure technology usage patterns 'in-situ', with improved ecological validity, to ascertain if individual differences such as, personality traits and demographics relate to different styles of use. It is also possible to assess if people have their own distinct smartphone usage patterns which are unique to themselves (see chapter five). In light of this, the following paragraphs describe how psychologists have studied personality and demographics in the past, to ascertain how they have become a key topic of interest in Psychoinformatics (Montag & Elhai, 2019).

1.5.2. Personality

Psychologists typically study a person's character or temperament through the lens of personality theory. Throughout the years, there has been divergent thinking regarding the origins and dimensionality of personality, but many often discuss the existence of stable personality traits (Mischel, Shoda, & Ayduk, 2008). Personality theory describes how individual traits are unique to the individual, which exist in a person's neurology and develop over the course of their life to guide and perform adaptive behaviour (Allport, 1962). Thus, no-one has the same individual traits, and this is the foundation of the ideographic approach to personality, which aims to obtain a rich understanding of the dynamic dispositions of the individual. Common traits on the other hand are "*those aspects of personality in to which most mature people within a given culture can be compared*" (Allport, 1962, pp. 300). They represent forms of adjustment that are a consequence of cultural pressures and can be defined as a collation of roughly comparable/synonymous individual traits (Allport, 1962). These, however, do not have a biological realisation, but are products of culture and language, and are abstract approximations of the individual (Allport, 1962).

Deciding what common traits to include in a taxonomy of personality whilst remaining parsimonious, holistic and generalisable to many people in a given culture, is one of the biggest challenges to personality psychologists. By the early 1990's, many psychologists found evidence for a five-factor solution of personality, consisting of the traits 'openness', 'conscientiousness', 'extraversion', 'agreeableness', and 'neuroticism' (Anglim & O'Connor, 2019). Each are measured on a continuous scale, and sample wide scores for each trait generally fit a normal distribution (Maltby et al., 2010). However, recent factor analysis research across several languages has suggested that six (rather than five) core personality characteristics exist and these are 'honesty-humility', 'emotionality', 'extraversion', 'agreeableness', 'conscientiousness', and 'openness-to-experience' (HEXACO) (Ashton, Lee, & de Vries, 2014). Reducing the study of personality to a handful of traits has large practical value; a person can be placed on a few key dimensions to build up a picture of what that person is approximately like as a whole. By adopting this 'nomothetic approach', the benefits of studying common traits include a generalisable study of human personality, with the ability to make direct comparisons between people. Consequently, chapters three and five explore how common traits using the HEXACO taxonomy relate to objective smartphone use.

1.5.3. Studying demographics

As well as personality traits, a person can be understood in terms of their demographics. Derived from the Greek words for people (demo) and picture (graphy) the term refers to characteristics of those in a population including age, gender, health, income, education, occupation, religion etc. (Salkind, 2010). Demography can be a useful tool in characterising people based on their sociological description, as they can be used to anchor associations with psychological concepts e.g., how age relates to subjective wellbeing (Easterlin, 2006). Whilst the reporting of demographics in psychology is mainly used to describe the representativeness of a given sample, psychologists can also use these variables to understand how demographic factors influence psychological phenomena such as infant development, mental health, intelligence, and technology use (Maltby et al., 2010). Therefore, in addition to personality traits, user demographics such as age and gender are also studied in this thesis (see chapters three, five and six) to provide a richer and more comprehensive understanding of how technology use can be indicative of people's characteristics.

1.5.4. Predicting Individual Differences

The study of demographics and common traits explore two key questions. "*What are the basic psychological qualities that characterize people*" and "*how can the consistent differences between people in these qualities be best captured and described*? (Mischel et al., 2008, pp.43). Notably, these questions are focused on describing the cognitions, sociological factors and behaviours which make people unique and do not necessarily concern themselves with the causes of these differences, such as genetics or past experiences (Fleeson & Jayawickreme, 2015). However, these descriptive endeavours on their own are important, as it has been argued that psychology's focus on the causes of behaviour may have led the development of strong theory, but on the other hand rarely has the capacity to predict future behaviour (Yarkoni & Westfall, 2017). Whilst this focus on prediction and description is not the prevalent paradigm in psychology, it has its own applied value which merits the adoption of this approach. For example, in security applications, the ability to predict the characteristics of an individual from digital traces when narrowing down a potential suspect from a large population pool can reduce workload. Predicting how a person may behave from mapping their characteristics can be used as an assessment of risk in security settings. Therefore, the ability to predict characteristics and behaviours from a set of digital variables can improve security outcomes.

By incorporating techniques such as machine learning algorithms from computer science disciplines as described in the Psychoinformatics approach, psychology can start incorporating prediction more centrally in its research practices to take advantage of its applied value (Yarkoni & Westfall, 2017). Therefore, chapter's three and five specifically investigate how technology use can predict characteristics about the user. Notably, chapter three explores whether simple meta data such as the smartphone operating system a person uses is enough information to start predicting characteristics. Chapter five explores whether stable use of applications across several days can act as a unique 'digital fingerprint' which allows for the identification of a specific user. This links back to the third objective of this thesis, by exploring how characteristics can be predicted from smartphone traces.

1.5.5. Psychoinformatics and Individual Differences

With the recent developments in Psychoinformatics and related fields, it is now posited that digital traces of behaviour could also be the standard measure of personality (Boyd, Pasca, & Lanning, 2020). Sometimes referred to as digital phenotyping, this approach takes digital data, such as Facebook likes, online conversations and smartphone use, and links these to personality characteristics (Montag & Elhai, 2019). The advantage here is to remove bias from self-report methodologies, if a person's disposition can be measured in a way that is removed from people's subjective experiences (Hinds & Joinson, 2019). Whilst some research takes digital data and then aims to predict if this is related to pre-existing personality theory, such as the five factor model, others are suggesting that new taxonomies of personality could be generated by clustering co-occurring behaviours from a set of digital traces collected on a user (Hinds & Joinson, 2019).

Of notable importance, people's real-world behavioural consistencies can be examined unobtrusively with high resolution by collecting behavioural traces (e.g., second by second smartphone use). As this digital data can represent people's behaviours outside the lab, this has made the study of situation-person interactions possible (Boyd et al., 2020; Montag & Elhai, 2019). Following suit, new studies can examine context dependent intraindividual stability of behaviour (see chapter 5), which was proposed nearly twenty years ago, but was difficult to study due to technological and computational boundaries (Mischel, 2004). Consequently, the incorporation of computer science approaches into the study of human dispositions has become the new agenda for personality research and makes up a large proportion of research outputs in Psychoinformatics (Montag & Elhai, 2019). In some cases, predictive computational models have shown to generate more accurate predictions of people's personalities than human observers (Youyou, Kosinski, & Stillwell, 2015). Consequently, chapters three, five and six follow this approach by linking smartphone usage to individual differences such as health, personality, and demographics, to ascertain if these digital traces can replace self-reports of individual differences.

1.6. This Thesis

In sum, this thesis has three main objectives. The first explores how studies of technology use can incorporate the collection of smartphone digital traces. How this may challenge or complement existing research which uses self-report methods of technology use is a prevalent theme across all chapters of this thesis. Secondly, this thesis aims to shift the narrative of solely studying smartphone use with a pathological lens. This was to demonstrate how documenting 'everyday' and 'common' smartphone use has its own value in psychological research and can further challenge existing positions which consider all smartphone use as problematic. The third objective of this thesis concerns itself with whether digital traces of 'everyday' smartphone behaviour can predict individual differences including a user's personality, demographics, and health.

The reasons behind these objectives were numerous. It is possible to re-address and query concerns regarding over-use of smartphone's with improved theoretical and methodological considerations. Additionally, if inferences can be made about a person's mental well-being, based on their smartphone usage, then this could lead to context-aware applications that could automatically instigate patient care. Furthermore, if smartphone use is indicative of a person's individual differences then this can be used to profile users and infer psychological states of criminals through their technology usage behaviours. Moreover, this research question indirectly encourages the methodological development of exploring objective smartphone use in psychological research. Therefore, addressing these objectives can generate several streams of insightful research.

1.6.1. Approaches and Methods used in this Thesis

This thesis uses an interdisciplinary approach, by adopting methodologies and paradigms from both psychology and computer science disciplines. Markedly, both fields have the shared interest of understanding how computer technologies interact with users to apprehend the societal impact of ubiquitous computing. However, whilst computer scientists typically focus on the promises of new technologies, social scientists tend to be critical and focus on the negative implications of its use (Davidson et al., 2019). It is proposed here that both disciplines would benefit from some ‘middle ground’, not only in regard to topic focus, but when it comes to methodological and analytical techniques.

When outlining how computer science can benefit psychological research, of particular pertinence here is smartphone data collection methods. However, as mentioned previously, the adoption of machine learning algorithms can help psychology become a science that can also predict behaviour and individual differences in a reliable manner. When predicting personality, typically computer scientists will collect a dataset of digital traces alongside personality assessments of the same users. Then the data is split into a ‘training’ data set and a ‘testing’ data set. By feeding the machine learning model training data, the model learns how to predict personality from digital traces. Then, the test data set is used to evaluate how accurate the model’s predictions are on ‘unseen’ data. This process is called cross-validation and the benefits of this approach include the evaluation of a model’s generalisability and reliability from the onset (Hinds & Joinson, 2019; Yarkoni & Westfall, 2017). If a model’s accuracy dramatically drops between test and training datasets, then it can be said the model has ‘overfitted’, meaning its predictions have become so precise to the training data, that they do not generalise beyond. Models are then ‘pruned’ to enhance generalisability. In psychology, statistical models are normally only assessed in regard to the data used to build or ‘train’ the statistical model, and therefore, do not include this reliability/generalisability check which aims to minimise prediction error (Yarkoni & Westfall, 2017). Consequently, it has been proposed that machine learning algorithms could be incorporated into the analysis of psychological research to help address the replication crisis (Yarkoni & Westfall, 2017). Decision tree algorithms, in particular, have other benefits as they do not assume that the contribution of each predictor variable has a linear association with the criterion variable and can therefore, be used to model variables which violate normality assumptions (Merkle & Shaffer, 2011). Consequently, a large proportion of this thesis uses predictive algorithms to ascertain how smartphone use is indicative of a person's individual differences.

Psychology, on the other hand, brings to computer science the testing of specific hypothesis and psychological intuition to the study of digital traces of behaviour. As previously remarked "*Technical aids should never be allowed to lower the basic requirement of psychological intelligibility*" (Allport, 1962, pp. 301). Notably, there is the temptation in computer science to collect as many digital traces as possible, to see if any relate to personality (Chittaranjan, Blom, & Gatica-Perez, 2013). Not only does this have ethical and privacy implications, but there may be no logical or theoretical reason as to why that trace would be reflective of personality. Psychology can improve the accuracy of predictive models by studying variables which have relevance to the phenomena in question. For example, machine learning algorithms are typically 'black box models' whereby, the mechanism behind how one variable predicts the other is unknown. However, it is possible to test the hypothesis that a variable will have predictive importance by introducing variables one at a time into a model to see if it improves accuracy (Yarkoni & Westfall, 2017). Chapter three in particular implements this idea using hierarchical regression modelling and permutation importance measures. As a result, throughout this thesis a variety of both ‘typical’ psychology and computer science analysis are adopted (see Table 1.1.)

Table 1.1. Methods used in empirical chapters

	Chapter 3	Chapter 4	Chapter 5	Chapter 6
Smartphone Measure	1) Analysis of smartphone operating system ownership	1) Archival smartphone use logs 2) Estimates of smartphone use 3) Problematic smartphone use scales 4) Continuous smartphone use logs	1) Continuous smartphone use logs	2) Archival smartphone use logs 3) Estimates of smartphone use 4) Problematic smartphone use scales 5) Continuous smartphone use logs
Methods	1) Online survey 2) In-person survey	1) Online survey 2) Laboratory tasks 3) Longitudinal Observation	1) Online survey 2) Longitudinal observation	1) Online survey 2) Bioimpedance assessment 3) Longitudinal observation 4) Archival activity data
Analysis	1) Hierarchical binary logistic regression, 2) Beta algorithm, 3) Conditional inference decision tree. 4) Conditional inference random forests. 5) Content analysis 6) Sentiment analysis 7) Wilcoxon rank sum	1) Spearman correlations 2) Wilcoxon signed ranks	1) Spearman and Pearson correlations 2) T-tests 3) Conditional inference forests 4) Behaviour profiling	1) Spearman correlations 2) *z* tests 3) Wilcoxon rank sum 4) Linear Regressions

1.6.2. Overview of chapters

The main premise of this thesis was to explore the question *"How can digital traces of 'everyday' smartphone use be indicative of a person's individual differences such as personality, demographics and health?"*. This led to several routes of exploration including novel theoretical developments, experimenting with new methodologies and several critical discussions regarding the state of psychological research when it comes to studying technology use and individual differences. This was achieved across several empirical, methodological, and theoretical chapters and a summary of each chapter can be found below.

Chapter 2 – The Technology Integration Model (TIM). Predicting the continued use of technology.

Computer scientists and Psychoinformatics researchers alike often demonstrate the predictive qualities of digital traces when it comes to identifying individual differences without any speculation as to why that relationship would exist. Moreover, existing theories of technology use in psychology do not hypothesise the mechanisms behind normal and everyday use. Chapter two aims to fill these gaps by developing a theory of continued technology use called the Technology Integration Model (TIM). Taking an interdisciplinary standpoint, the chapter reviews existing theories of technology use and develops a new model using a unification methodology that was developed for the purpose of this chapter. As part of this, the chapter explores a concept called 'extended self' to help explain the human-computer relationship, and then uses this to outline how individual differences transfer to digital traces. Smartphones can be said to amalgamate with its user via principles of extended self, and it is posited that this integration explains why smartphone usage behaviours could predict users' individual differences. Thus, chapter two presents TIM alongside a description of its scope and the relationships between constructs. TIM's focus on everyday use, alongside longitudinal and direct measurements of technology use can help generate novel research questions while simultaneously addressing many previous shortcomings of existing models. Consequently, this chapter sets the theoretical grounding for the rest of the thesis.

Chapter 3 – Smartphone OS and the Extended Self

Android and iPhone devices account for over 90 percent of all smartphones sold worldwide. Despite being very similar in functionality, current discourse and marketing campaigns suggest that key individual differences exist between users of these two devices; however, this has never been investigated empirically. Chapter three begins the journey of exploring how technology use relates to a person's individual differences by studying whether the most basic digital trace, the operating system a person is using, is informative enough to predict characteristics. This is in direct contrast to existing computer science studies which record numerous digital traces from a user's smartphone. If a simple, non-intrusive digital trace can perform the predictive requirements needed to map a person's characteristics, then this may reduce the need for more invasive tracking. In comparison to Android users, it was found that iPhone owners were more likely to be female, younger, and increasingly concerned about their smartphone being viewed as a status object. Key differences in personality were also observed with iPhone users displaying lower levels of 'honesty-humility'. Thus, in line with the Technology Integration Model, the type of smartphone owned provided some valuable information about its user.

Following this analysis, the chapter describes the building and testing of algorithms that predicted smartphone ownership at above chance level based on these individual differences. Furthermore, the chapter explores whether stereotypes had formed regarding the characteristics of users of each smartphone OS brand. These stereotypes were largely inaccurate when compared to findings from study one, suggesting that computer algorithms could out-perform human observers when identifying differences between users. Consequently, the findings from this chapter have privacy and ethical applications for companies that use cookies and other means to track information and characteristics about its users. In academia, these findings have further implications when using smartphones in Psychoinformatics research, where data is typically collected from devices and applications running a single smartphone operating system. Where possible, the rest of this thesis collects data on both iPhone and Android users.

Chapter 4 – Exploring objective measures of smartphone use

It remains a pivotal research endeavour to understand how people use technology in order to adequately measure the impact this might have on individuals and society. However, research exploring this question in psychology and social science disciplines overwhelmingly relies on self-report measures of smartphone use, despite the availability of tools and programming frameworks now available to document use directly. Whether self-reports can be used as an adequate substitute for objective measures is yet to be assessed. Therefore, chapter four addresses this methodological question by assessing whether temporal estimates of smartphone use, and a suite of psychometric scales have the ability to predict objective smartphone behaviour. This was explored across both iPhone and Android users by collecting actual usage logs from Apple Screen Time and a custom-built Android application made using the FunF programming framework. Study one showed correlations between self-reports and objective smartphone behaviours were generally poor, with a single estimate of use out-performing psychometric scale measures.

Study two then further explored the accuracy of subjective estimates by comparing them to second-by-second logs of smartphone usage behaviours in android owners. Due to greater temporal resolution, it was possible to define what a smartphone check consisted of, and this was any use lasting under 15 seconds in duration. Findings showed those who used their phone a lot tended to underestimate their phone use, and those who used their phone a little tended to overestimate across both daily checks and daily screen time variables. Exploratory analysis also found that smartphone usage behaviours were relatively consistent on a day-to-day basis. Five days of data was shown to be representative of a person's overall usage examining daily screen time. However, when observing either smartphone pickups or checks, researchers only need to collect to two days' worth of data. Consequently, this methodological chapter provided a route forward in this thesis in terms of how to measure technology usage behaviours in a valid and reliable manner.

Chapter 5 – Predicting individual differences from smartphone use.

Gathering data about the attributes of a person or group typically relies on self-report personality questionnaires. However, new approaches in behavioural science describe how analysing digital traces of behaviour from mobile devices and online activity can be used to produce personality assessments. This chapter therefore asks the question *"After smartphone operating system, what is the most basic digital trace that can be assessed to ascertain if it provides information about a user's individual differences?"*. This instigated an exploration of whether a simple log of smartphone screen state and application use is indicative of user's personality traits and demographics. 46 android users installed a custom-built logging application which monitored their smartphone usage behaviours for seven days. Participants also completed the HEXACO personality questionnaire. The results found that demographic variables such as age and gender were better predictors of objective smartphone use than personality traits. Thus, in contrast to predictions, findings showed that it was difficult to predict a user's personality traits from screen time and application usage measures alone, with significant findings being scarce across the numerous correlations conducted.

On the contrary, exploring personality through the use of ideographic approaches had greater promise. To elaborate, longitudinal and context dependent assessments are largely absent when it comes to understanding the processes that underpin trait characteristics. However, further exploratory analysis in chapter five showed that within-subject smartphone use was highly consistent and unique to the individual. This within person homogeneity and across person heterogeneity made it possible to identify users accurately from a single day of usage, when trained on just under a week's worth of data. This was apparent for both daily checking and application usage behaviours. The ability to identify an individual from a crowd when given anonymous smartphone data showed that individuals have unique smartphone use personalities that leave behind a 'digital fingerprint'. Consequently, in the digital age, this chapter supports dynamic personality theories which describe context dependent intraindividual stability of behaviour.

Chapter 6 – Quantifying smartphone 'use': Choice of measurement impacts relationships between 'usage' and health.

Chapter four of this thesis suggested that self-report assessments of smartphone use were unlikely to be sensitive enough to accurately predict basic smartphone use behaviours. This brings into question the conclusions of previous studies which have used these methods to make claims regarding technology's impact on health. Chapter six therefore considered whether different ways of measuring 'smartphone use', notably through problematic smartphone usage (PSU) scales, subjective estimates, or objective logs, leads to contrasting associations with mental and physical health. In study one, measures of mental health and body composition were completed by participants and compared to psychometric scales, estimates, and objective logs of smartphone use. The results were then used to generate hypotheses regarding the influence of different usage measurements on effect sizes. A second study then acted as a replication and provided increased statistical power. Across both studies, it was observed that measuring smartphone interactions with PSU scales produced larger associations between mental health when compared with subjective estimates or objective logs. Notably, the size of the relationship was fourfold in Study 1, and almost three times as large in Study 2 when relying on a smartphone addiction scale instead of objective measures. Further, in regression models, only smartphone addiction scores predicted mental health outcomes, whereas objective logs or estimates were not significant predictors. The chapter concludes that addressing people's concerns about their technology usage is likely to have greater mental health benefits than reducing their overall smartphone use, and that mental health symptomology cannot be predicted from general smartphone behaviours.

Chapter 7 – Discussion

Chapter seven brings this thesis to a close by providing a final overview of the contributions made by each chapter as a collective, to discuss challenges and future directions when ascertaining individual differences from digital traces of behaviour. Key research questions are revisited and critically discussed in light of novel findings. Specifically, health, personality and demographics are discussed separately when understanding how digital traces relate with each. Furthermore, a large part of chapter seven discusses the strengths and limitations of objective smartphone measures, and how data science techniques can advance analysis methods in psychology. In addition, measuring digital traces has new ethical considerations which requires acknowledgement if researchers continue to study them. Finally, the future of using digital traces in personality research in particular is discussed, and a potential framework which could be adopted in upcoming exploratory work is outlined. The thesis concludes by stating that the incorporation of computer science methodologies in psychological research, allows for endless possibilities for testing and extending psychological theory in the digital age.

Chapter 2

The Technology Integration Model (TIM). Predicting the Continued Use of technology.

The following chapter forms part of the publication: Shaw, H., Ellis, D. A., & Ziegler, F. V. (2018). The Technology Integration Model (TIM). Predicting the continued use of technology. *Computers in Human Behavior*, *83*, 204-214. https://doi.org/10.1016/j.chb.2018.02.001

2.1. Introduction

2.1.1. Developing a new theory of technology use.

As widely discussed in the introduction, it has become increasingly important to understand the relationship people have with technology. Many positive effects have arisen from technology use such as social inclusion, increased access to information, assistance with every-day tasks, and healthcare applications (Andrade & Doolin, 2016; Khosravi, Rezvani, & Wiewiora, 2016; Kirkpatrick, 2016; Piwek, Ellis, Andrews, & Joinson; 2016). In contrast, negative side effects have been reported such as technology addiction, perceived privacy breaches, reduced physical activity, online shaming and unsatisfactory work-life balance (Akdemir, Vural, Çolakoğlu, & Birinci, 2015; Bergström, 2015; Clayton, Leshner, & Almond, 2015; Jeong, Kim, Yum, & Hwang, 2016; Klonick, 2016; Mamonov & Benbunan-Fich, 2014; Osiceanu, 2015; Schoneck, 2015; Steijn & Vedder, 2015). Yet, in the field of Psychology and Cyberpsychology more specifically, there is scarce theoretical understanding explaining why people use technology, and furthermore, the impact this has on users (Orben, 2018).

Predominately, focus has been placed on understanding pathological technology use such as problematic "Facebooking", microblogging, gaming, pornography use, smartphone use, text messaging, and pathological use of social networking sites (Andreassen, 2015; Guedes et al., 2016; Hou et al., 2014; Kaptsis, King, Delfabbro, & Gradisar, 2016; Kwon et al., 2013; Ševčíková, Blinka, & Soukalová, 2018; Sultan, 2014). Consequently, theoretical perspectives have primarily adopted a behavioural addiction approach which describes how all addictions which do not involve ingesting a substance are said to have the same underlying components: salience, mood modification, tolerance, withdrawal, conflict, and relapse (Griffiths, 2005). This framework has been extremely influential and generated two decades of research concerning technology addiction (Mihajlov & Vejmelka, 2017). The popularity of this approach can be attributed to the fact that the same underlying framework can apply to a multitude of different problematic behaviours (Griffiths, 2005; Ryding & Kaye, 2018). There is also a wide range of assessment tools developed to measure technology addiction, that are easily implemented via self-report, and can be pulled quickly into new and existing research projects (Ellis, 2019; Mihajlov & Vejmelka, 2017). This popularity alone has arguably led to government enquiries investigating the growth of 'immersive and addictive technologies' almost pre-empting a future public health problem (DCMS-Committee, 2018).

However, what is largely ignored is an understanding of everyday 'none-pathological' technology use. The majority of the population describe the internet as an essential part of their lives and would feel cut off and lost without it (OFCOM, 2018). People use emails, Google Docs, Skype, and search engines for work related purposes (Widdicks, Ringenson, Pargman, Kuppusamy, & Lago, 2018). Similarly, podcasts, on demand content, streamed music, internet games, hobby sites, social media sites and instant messaging services provide entertainment and social interaction (Widdicks et al., 2018). Furthermore, recent trends suggest that this is not going to change as there is an ever-increasing number of everyday objects that connect to the internet (e.g., the internet of things) (Bergman, 2015).

Despite this, the relationship between people and 'everyday' technology use remains poorly defined from a theoretical standpoint. This could be of value when developing new technologies and would provide a fuller understanding of their impact. In addition, the fundamental reasons behind technology use have often been difficult to define, despite the prevalence of technology in society. Even specific factors which influence or predict future use remain contentious (Karahanna, Straub & Chervany, 1999; Ding, Chai & Ng, 2012). However here, through the evaluation of previous theoretical models, a new integrated theory of continued technology use and technological impact is proposed.

Once theories are able to provide a psychological understanding of what predicts certain technology usage patterns, it is then possible to understand why technology use variables can be indicative of user characteristics and be predictive of their individual differences. For example, if a person's motivations, age, personality traits, and routines, are precursory of their technology use, then the way a person uses their technology is likely to relate back to their individual differences. Specifically, Belk's extension of self-theory suggests we place part of our self-identity in the technology we use due to the way we personalise and manipulate it (Belk, 2013). To summarise, this approach posits that 'human factors' which predict the use of a particular technology, including a person's demographics and personality traits will be evident in their technology usage (or none usage) patterns.

2.1.2. Existing Theories of Technology Use

As the applications of studying technology use span widely, there has been a shift in the literature (in disciplines outside of psychology) from measuring technology adoption to measuring technology use (Ding, Chai & Ng, 2012). Often, the continued use of a technology is seen as an extension of the adoption process, suggesting both adoption and post-adoption behaviours can be measured using the same variables (Davis, Bagozzie, & Warshaw, 1989; Venkatesh, Morris, Davis & Davis, 2003; Venkatesh, Thong & Xu, 2012; Venkatesh, Thong & Xu, 2016). The most popular theory that predicts technology adoption and future-use is the technology acceptance model (TAM) (Marangunic & Granic, 2015). TAM contains several variables such as perceived usefulness, perceived ease of use, external variables, attitude, and behavioural intention as precursors of technology adoption and use (Davis, Bagozzie, & Warshaw, 1989).

However, the variables which predict technology adoption have been shown to differ from the variables which predict continued technology use (Limayem, Cheung & Chan, 2003). For example, a person's attitude towards a technology before adoption is often influenced by perceptions of usefulness, ease of use, result demonstrability, visibility and trialability, whereas attitudes after adoption are influenced by instrumental beliefs of usefulness and perceptions of image enhancements (Karahanna, Straub & Chervany, 1999). As such, it appears that continued technology use is not just a continuation of technology adoption, but a phenomenon within itself. This raises additional questions regarding the suitability of TAM and successive extensions when measuring any technology use after initial adoption.

After citing the original TAM model, many researchers simply extend it by including additional variables of their own choosing, which they perceive to have particular relevance to the technology being assessed. (Jafarpour, 2016; Ooi & Tan, 2016; Ramos-de-Luna, et al., 2016; Tsai, Chang & Ho, 2016; Wang & Sun, 2016; Yoon, 2016). This is because theoretical and empirical work often struggles to keep up with the speed of technological development, and therefore, any theory is very quickly adapted and changed so it can be applied to contemporary technologies. This can make subsequent generalization difficult. To emphasise this point, a 2007 meta-analysis generated a list of 78 external variables that had been added to TAM with the aim to predict perceived ease of use and perceived usefulness across various contexts (Yousafzai et al., 2007a). Examples of these included 'Screen Design', 'Management Support', 'Organizational Policies', 'Cognitive Absorption', and 'Cultural Affinity' (Yousafzai et al., 2007a). There is no coherent trend regarding which variables are included in these models. Consequently, the reliability of variables cannot be assessed due to a lack of succeeding confirmatory research. The development of any new theory must therefore be inclusive of key constructs which predict the use of current and future technologies. In turn, this will also become a platform for researchers to re-test the same concepts and improve our understanding of continued technology use.

2.1.3. Theoretical Unification

Several theories of continued use describe a set of variables which predict technology adoption, and then include additional variables to the initial model to explain continued use (Setterstrom, Pearson & Orwig, 2013; Kim & Crowston 2011). Others consider continued use in isolation as its own behaviour (Bhattacherjee, 2001; Limayem, Cheung & Chan 2003). A theoretical unification approach of variables described in these theories was chosen to generate a new model (Table 2.1.) (Venkatesh, Morris, Davis & Davis, 2003). This acknowledges both existing work and evidence that can contribute to our understanding of continued technology use. However, merging existing theories can sometimes lack the novelty required to provide new research directions that expand our knowledge. Therefore, this chapter aimed to merge competing theories into a singular comprehensive model of technology use and impact, whilst incorporating psychological constructs which have never been considered in existing technology use models. What makes the current unification different from previous attempts including the UTAUT, UTAUT2 and the Multilevel Framework of Technology Acceptance and Use (Venkatesh, Morris, Davis & Davis, 2003; Venkatesh, Thong & Xu, 2012; Venkatesh, Thong & Xu, 2016), is its retained parsimony, its focus on technology use rather than adoption, and the inclusion of novel insights which describe the impact that technology has on people. To inspire the new model, key groups of variables will be identified across existing technology use theories. A novel variable called extended-self is introduced, which is proposed to predict continued technology use, (Steinert, 2015; Belk, 1988, 2013; Clark & Chalmers, 1998). The scope of new model is then defined, presented and discussed in detail.

Table 2.1. Proposed steps for ensuring quality when unifying theories.

Unification Step	Description	Rationale
Outline Phenomenon	Describe the phenonmenon needed to be explained and why this is important. Consider why is it useful to abstract and simplify the particular phenomenon for human comprehension. Identify those who would benefit from your theory, and how it would be utilised.	For a theory to be useful, it must have some academic or real-world value. A theory should be a “tool” and have practical uses.
Key Predictor Variables	Review the literature, by searching for previous theories and research which have predicted the phenomenon. Then, through evaluative mechanisms identify key themes.	This incorporates the unification of synonymous variables, whilst providing a summary of existing salient ideas which predict the phenonema under investigation. This ensures a new theory is comprehensive, whilst ensuring listed variables are independent from one-another.
New Insights	Are there any new varaibles or relationships which could be incorporated to help increase the explanatory power when predicting the phenonmenon?	This allows for the phenomenon to be perceived and tested in a way which hasn’t previously been done. This is important as it can create new knowledge.
Outline Scope of New Theory	What are the limits to your theory? A theory can only explain so many concepts. Identify the scope of your theory and also define what your theory does not explain.	Unification models can easily become a “jack of all trades” and try and explain everything which leads to the phenomenon. This makes it difficult to put into practice and also effects understanding as insights are diluted across many variables.
Construct Selection	Now that the scope of your new theory has been outlined, there will be variables which no longer are relevent to its aims. Can any variables be re-worded, merged or changed to better suit these aims?	Parsimony; ensures all constricts fit with the scope of the new model and rejects irrelavant variables.
Review Associations	Find evidence or create new insights as to how the proposed variables are related. Work backwards from the phenonenon to be predicted, and consider the scope of your theory, and what is relevant.	This allows for clear and relevant hypothesis to be formulated.
Present New Model	Describe and visually present the new model, ensuring all constructs and relationships are clearly defined.	This provides researchers a new tool to test the same concepts and formulate research questions. It may also be a tool for other stakeholders.

2.2. Review of Existing Literature

2.2.1. Key Predictor Variables

To identify key themes, 11 models of continued technology use were reviewed, and their variables extracted (Table 2.2.). Theories were found by using the search term 'continued technology use' when searching the library's collection of online articles, at the University of Lincoln in the summer of 2017. Further theories were found through reading these articles. Models were not included in this review if they only predicted technology adoption, as the aim was to understand usage beyond this point. In these theories, numerous variables were proposed to influence continued use such as satisfaction, habits, and affective reaction (Bhattacherjee, 2001; Limayem Cheung & Chan, 2003; Kim & Crowston, 2011). Some variables across models were synonymous or could be grouped in a more general construct, allowing for consistent testing. This permits the generation of key themes or groups of variables. The purpose of this was to provide a summary of existing salient ideas which predict technology use, that can be used in the development of future theories. Overall, 14 key variables resided across models (Table 2.2.). Therefore, it is possible to create a new and comprehensive model of technology use, by taking inspiration from these key themes.

Table 2.2. Identification of key technology use variables by combining synonymous variables across models.

Key Theme	Variables Included	Link
Ease of Use	Effort Expectancy (Venkatesh, Morris, Davis & Davis, 2003; Venkatesh, Thong & Xu, 2012), Perceived Ease of Use (Kim & Malhotra, 2005; Davis, Bagozzi & Warshaw, 1989; Venkatesh & Davis, 2000), Objective Usability (Venkatesh & Bala, 2008) and Technicality (Setterstrom, Pearson & Orwig, 2013).	Effort, ease, or difficulty of performing a technology use behaviour.
Pre – Use Evaluations	Attitude (Kim & Crowston, 2011; Davis, Bagozzi & Warshaw, 1989), Performance Expectancy (Venkatesh, Morris, Davis & Davis, 2003; Venkatesh, Thong & Xu, 2012), Perceived Value (Setterstrom, Pearson & Orwig, 2013) and Result Demonstrability (Venkatesh & Davis, 2000; Venkatesh & Bala, 2008).	Evaluating the technology before use.
Behavioural Intention	Behavioural Intention (Kim & Malhotra, 2005; Davis, Bagozzi & Warshaw, 1989; Venkatesh & Davis, 2000; Venkatesh, Morris, Davis & Davis, 2003; Venkatesh, Thong & Xu, 2012; Venkatesh, Thong & Xu, 2016) and Continuance Intention (Limayem, Cheung & Chan, 2003; Setterstrom, Pearson & Orwig, 2013; Bhattacherjee, 2001).	A person's intentions to use the technology
Technology Use Behaviours	System Use (Kim & Malhotra, 2005; Davis, Bagozzi & Warshaw, 1989), IS Continuance (Limayem, Cheung & Chan, 2003) and Use Behaviour (Venkatesh & Davis, 2000; Venkatesh, Thong & Xu, 2012).	Actual technology use.
Context	Environmental Attributes, Location Attributes, Events (TIME) and Organisational Attributes (Venkatesh, Thong & Xu, 2016).	Contextual factors that could influence use.
Support	Perceptions of External Control (Venkatesh & Bala, 2008), Facilitating Conditions (Venkatesh, Thong & Xu, 2012; Venkatesh, Morris, Davis & Davis, 2003; Venkatesh, Thong & Xu, 2016), and Organisational Attributes (Venkatesh, Thong & Xu, 2016).	Support mechanisms available, which could aid the use of the technology.
Extrinsic Motivations	Perceived Usefulness (Kim & Malhotra, 2005; Limayem, Cheung & Chan, 2003; Setterstrom, Pearson & Orwig, 2013; Bhattacherjee, 2001; Davis, Bagozzi & Warshaw, 1989; Venkatesh & Davis, 2000), Job Relevance (Venkatesh & Davis, 2000; Venkatesh & Bala, 2008), task attributes (Venkatesh, Thing & Xu, 2016) and Objective Usability (Venkatesh & Bala 2008).	Practical advantages of using the technology to complete specific tasks.

Table 2.2 Continued: Identification of key technology use variables by combining synonymous variables across models.

Key Theme	Variables Included	Link
Intrinsic Motivations	Enjoyment (Setterstrom, Pearson & Orwig, 2013), Uncertainty Avoidance (Setterstrom, Pearson & Orwig, 2013), Affective Reaction (Kim & Crowston, 2011) Perceived Enjoyment (Venkatesh & Bala, 2008) and Hedonic Motivations (Venkatesh, Thong & Xu, 2012).	Internal experience that is the result of using the technology.
Habit	Repeated Behavioural Patterns (Kim & Malhotra, 2005) and Habit (Limayem, Cheung & Chan, 2003; Setterstrom, Pearson & Orwig, 2013; Kim & Crowston 2011; Venkatesh, Thong & Xu, 2012; Venkatesh, Thong & Xu, 2016).	Habitual mechanisms which drive technology use.
Individual Differences	Experience (Venkatesh & Davis. 2000; Venkatesh & Bala, 2008; Venkatesh, Morris, Davis & Davis, 2003; Venkatesh, Thong & Xu), Computer Self Efficacy (Venkatesh & Bala, 2008), Computer Anxiety (Venkatesh & Bala, 2008), Computer Playfulness (Venktesh & Bala, 2008), Gender (Venkatesh, Morris, Davis & Davis, 2003; Venkatesh, Thong & Xu, 2012), Age (Venkatesh, Morris, Davis & Davis, 2003; Venkatesh, Thong & Xu, 2012) and User Attributes (Venkatesh, Thong & Xu, 2012).	Attributes of the user which may influence the use of a technology.
Post-Use Evaluations	Feedback Mechanisms (Kim & Malhotra, 2005) Sequential Updating Mechanisms (Kim & Malhotra, 2005), Confirmation (Limayem, Cheung & Chan, 2003; Bhattacherjee, 2001), Satisfaction (Limayem, Cheung & Chan, 2003; Bhattacherjee, 2001), Cognitive Reaction (Kim & Crowston, 2011) and Output Quality (Venkatesh & Bala 2008; Venkatesh & Davis, 2000).	Evaluating the technology after use, which may influence future behaviour.
Price	Perceived Fee (Setterstrom, Pearson & Orwig, 2013) and Price Value (Venkatesh, Thong & Xu, 2012).	Monitory costs associated with using the technology.
Social Factors	Subjective Norms (Kim & Crowston, 2011; Venkatesh & Davis, 2000; Venkatesh & Bala, 2008), Image (Venkatesh & Davis, 2000; Venkatesh & Bala, 2008) and Social Influence (Venkatesh, Morris, Davis & Davis, 2003; Venkatesh, Thong & Xu, 2012).	A user's perceptions of how others view them if they were to use the technology.
Mandatory Use	Voluntariness (Venkatesh & Davis, 2000; Venkatesh & Bala, 2008; Venkatesh, Morris, Davis & Davis, 2003).	If the user perceives using the technology to be mandatory.

2.2.2. Additional Variable: Self-Extension

What remains absent in existing theories is an explanation of the core human-technology relationship. Stone tools were invented by our solution seeking homo habilis ancestors 2.5 million years ago (Mazur, 2002), and tool use suggests that human nature is inherently 'cyborg' as primitive technology can extend a person's physical capabilities and is not a phenomenon constrained to science-fiction (Wells, 2014). Specifically, self-extension has repeatedly been shown to be important when it comes to explaining the psychological impact of owning goods and digital services (Sheth & Solomon, 2014). Cognitive neuroscience studies provide evidence for the existence of extended self, as tool use has been shown to extend our physical body schema; our neuronal representation of our body size, shape, location, and movement in environmental space (Iriki, Tanaka, & Iwamura, 1996).

Self-extension describes how technology, possessions, and tool use extend who we are as humans and people (Steinert, 2015; Belk, 1988, 2013; Clark & Chalmers, 1998). The part of the human to be extended varies across previous theories as the mind (Clark & Chalmers, 1998), body (Steinert, 2015) and identity (Belk, 1988, 2013) have formerly been argued to be extended through using and owning objects. Smartphones have been shown to extend cognitions, as those who think more intuitively and less analytically when solving problems are more likely to use their smartphone in everyday situations to retrieve information (Barr, Pennycook, Stolz, & Fugelsang, 2015). Participants have also reported that mobile phones extend their self-identity, and this extension occurred more when their phone was in their possession in comparison to when separated from their phone (Clayton, Leshner & Almond, 2015).

The variable ‘Extended Self’ has received growing attention since originally proposed by Belk (1988) (Schultz, 2014). By describing how people feel a claim and ownership over objects, extended self-ideas depict the core relationship between the technology and the owner which no other variable in the review encapsulates. This variable is unique because it suggests there is a key psychological amalgamation with a technology in a user’s possession, that has yet to be applied to technology use. This could, in turn, provide new insights in terms of how self-extension via technology use carries over into continued usage.

2.3. Theoretical Construction

2.3.1. Scope

Unification models can easily become a “jack of all trades” in an attempt to explain all factors that lead to the phenomenon under investigation (Venkatesh, Thong & Xu, 2012). Theories often lack parsimony as insights are diluted across many variables/constructs which can negatively impact understanding of the described phenomenon (Venkatesh, Thong & Xu, 2016). Thus, the focus of this new theory is to describe factors which influence an individual user when predicting technology use. Explaining the spread of technology in an organization or a specified society will not be considered in this model due to the expanse of variables which would need to be incorporated.

The new model (Figure 2.1.) is entitled the Technology Integration Model (TIM) and the main objective of TIM is to outline the processes behind continued technology use, also referred to as post adoption use, in an individual's everyday life. TIM examines how technology integrates with its user over time via the model iterating repeatedly until the technology is abandoned or replaced. The constructs in TIM predict technology use in the few moments before a technology is used/not used. This is advantageous as this model does not aim to predict intentions or attitudes towards using the technology but aims to predict the precursors of actual behaviour. TIM describes the use-cycle of a singular technology. It is likely that a user will have several technologies at a time and thus, will have one predictive use-cycle for each of their devices.

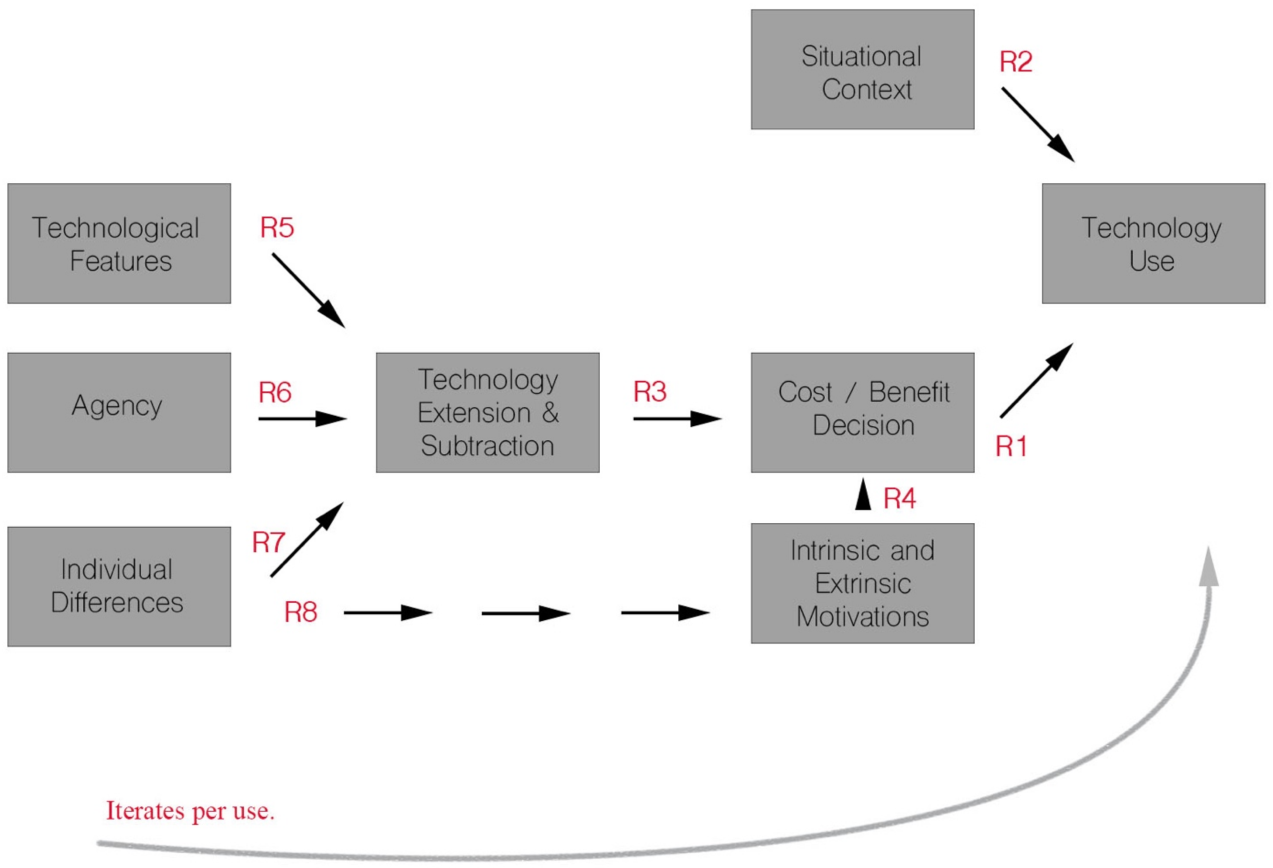

Figure 2.1. The Technology Integration Model (TIM).

2.3.2. The Technology Integration Model (TIM)

The previous literature review and the exploration of a new variable, extended self (Belk, 1998), has inspired the creation of The Technology Integration Model (TIM). TIM proposes that there are two direct predictors of technology use, which are, a cost-benefit decision (R1) and situation context (R2). Over time, it is proposed that the more a technology becomes habitual through repeated use, situational context will become more predictive and the cost/benefit decision will become less predictive of technology use. This is because when the decision to use a technology becomes less conscious, use is prompted by contextual cues (Stawarz, Cox & Blandford, 2015). This allows us to understand how technology use can become habitual. In previous research, the variables 'habit' and 'perceived value', which are two variables conceptually similar to situational context and the cost-benefit decision, have been shown to explain 71% of the variance in continued use of a web-enabled wireless technology (Setterstrom, Pearson & Orwig, 2013). Therefore, there is already strong empirical evidence to suggest that the combination of cost/benefit decision making, and technology use in response to habitual cues such as situational context will be able to explain a large proportion of technology use variance.

TIM continues to describe what influences the cost-benefit decision, namely, technology extension & subtraction (R3) and intrinsic & extrinsic motivations (R4). Thus, if a technology adds affordances to a person, which helps satisfy their intrinsic and extrinsic motivations, it will be considered worth using, prompting use. TIM further discusses what predicts technology extension and subtraction, to help understand the positive and negative effects technology can have on a user. Overall TIM has eight variables including technological features, agency and individual differences which are shown in Figure 2.1. as predictors of technological extension and subtraction (R5, R6 & R7 respectively). Finally, individual differences are said to be predictive of a person's motivations (R8). All relationships are currently described as connections as research is needed to determine whether they are moderating or mediating relationships. The development and precise definition of the variables in TIM are outlined in the following section.

2.3.3. Variable Development

By focusing on technology use separate from adoption, it is possible to isolate variables that predict subsequent usage. This facilitates the creation of a more parsimonious model, when compared to previous theories that attempt to combine both, such as the Unified theory of Technology Adoption and Use (UTAUT), the UTAUT2 and the Multi-Level Framework of Technology Acceptance and Use (Venkatesh, Morris, Davis & Davis, 2003; Venkatesh, Thong & Xu, 2012; Venkatesh, Thong & Xu, 2016). The variables defined in TIM have been chosen from the key themes review (Table 2.2.) and adapted due to their relevance when considering the scope of the model (section 2.3.1.). The following section will outline the development of the constructs included in the new model as a result of reviewing previous theories.

2.3.3.1 Technological Features

Existing technology use models rarely focus on the features that a technology contains. In the review, only one model, the Multi-level Framework of Technology Acceptance and Use, discussed the importance of this (Venkatesh, Thong & Xu, 2016). Their variable, Technology Attributes, emphasises how the overall functions, characteristics and features of a technology plays a role in continued technology use. (Venkatesh, Thong & Xu, 2016). TAM vaguely describes how the features of a technology influence technology adoption and use by stating that a technology's perceived ease of use predicts the behavioural intention to use the technology (Davis, Bagozzi & Warshaw, 1989). However, this appears oversimplified, and ignores the description of useful features, which could be included in the design of technology. For example, one study asked information system researchers their opinion on TAM, with one participant stating that *"TAM's simplicity makes it difficult to put into practice ... imagine talking to a manager and saying that to be adopted, technology must be useful and easy to use"* (Lee, Kozar & Larsen, 2003, p. 766). Therefore, the formation of the variable 'technological features' aims to provide descriptive knowledge which can be used to guide the design and implementation of technology. Arguably a theory of human-computer interaction must incorporate both human and technological feature(s) variables that may influence the use of technology.

Technology features are therefore, defined here as a technology's hardware and software properties. Technologies have a large array of features, for example: input modality, visual display, device connectivity, sensors, sharing features, device interactivity with the environment, storage, ergonomics, build material and engineered physical movement etc. The features a technology may possess will change as technology advances, and therefore, this construct is required to have a wide scope to ensure it stays relevant for future technology. This differs slightly from the definition of technology attributes in prior work (Venkatesh, Thong & Xu, 2016) as the functions of a technology are described in a separate variable, technology extension and subtraction. Therefore, Technology Features is very descriptive of the features a technology has. Whilst the construct technology features may be considered broad in nature, it is possible to repeatedly test the hypothesis that technology features influence technology use (or in TIM technological extension and subtraction), regardless of the technology features under investigation. This allows the theory to be adaptive to future technologies, as its difficult to pre-empt the technology of the future.

2.3.3.2. Agency

Agency has been defined as *"the experience of controlling both one's body and the external environment"* (Limerick, Coyle & Moore, 2014, p. 1). However, feelings of control also resonate in several synonymous technology use variables such as effort expectancy, perceived ease of use, and technicality (Davis, Bagozzi & Warshaw, 1989; Venkatesh & Davis, 2000; Venkatesh, Morris, Davis & Davis, 2003; Kim & Malhotra, 2005; Venkatesh. Thong & Xu, 2012; Setterstrom, Pearson & Orwig, 2013). Whilst all referring to the effort, ease, or difficulty of performing a technology use behaviour, it is possible that core to all these variables is the idea of agency over the technology we use, as issues with usability leave the user with a lack of control over the technology. A recent review confirmed that a feeling of agency is fundamental when encouraging human-computer interaction. Limerick, Coyle, and Moore (2014) discusses concepts such as intentional binding, gulf of execution, system reliability, system feedback, latency, task automation and embodiment which can affect the feelings of agency. These concepts are reminiscent of the criterion proposed for a technology to extend a person's mind which include trust, accessibility, reliability, and availability of the technology (Clark & Chalmers, 1998). As this theory focuses on human-computer interaction as a new direction when comprehending technology use, it is deemed important to include agency in the model. A sense of agency may, furthermore, explain previous findings concerning why ease of use predicts system use and technology usage intentions, a finding consistently shown through testing the TAM model (Yousafzai, Foxall & Pallister, 2007b). Finally, significant to the extension of self-theory is a sense of agency over the technology we use (Belk, 1988, 2013). This idea was first proposed by McClelland (1951) who stated that the more control you exert over an object or technology, the more incorporated an object becomes part of a person's self-identity.

2.3.3.3. Individual Differences

Individual differences can include personality traits, demographics and other variables that can be used to describe the end user. Other examples might include a person's time management, mental & physical health, cognitive functioning, skills, mood, age, personality, social relationships, social economic status, occupation, culture, wealth, and environment. Shneiderman and Plaisant (2004) discuss how *"all design should begin with an understanding of the intended users, including population profiles"* (p. 67). Furthermore, people learn, think, and solve problems through varying methods and will prefer certain types of technology over others (Shneiderman & Plaisant, 2004). Consequently, understanding a user by analysing their individual differences is pivotal. Individual differences have appeared in a variety of forms throughout existing models through the variables: experience, computer self-efficacy, computer anxiety, computer playfulness, gender, and age (Venkatesh & Davis, 2000; Venkatesh, Morris, Davis & Davis, 2003; Venkatesh & Bala 2008; Venkatesh, Thong & Xu, 2012)

The most recent model reviewed, 'A Multi-level Framework of Technology Acceptance and Use', merged the moderating effects of age, gender and experience into a singular variable called 'User Attributes'. This was the result of researchers extending the Unified Theory of Acceptance and Use of Technology to encompass more demographics, to the point where it was no longer practical to test (Venkatesh, Thong & Xu, 2016). As a result, the model was more flexible and included other demographical variables such as occupation and user type (e.g., employee, consumers, and citizens). Whilst the construct individual differences may be considered broad in nature, it is possible to repeatedly test the hypothesis that individual differences influence technology use (or in TIM technological extension and subtraction), regardless of the individual difference under investigation. As a result, researchers are not required to expand the constructs in the model due to a lack of comprehensiveness. The advantage of exploring a wide range of individual differences is that it becomes possible to discover which are the most important and influential when predicting technology use and does not place boundaries on the vast number of individual differences that can be included. This will aid the current theory to be generative in future research.

2.3.3.4. Technology Extension and Subtraction

Technology has been said to extend a person (Steinert, 2015; Belk, 1988, 2013; Clark & Chalmers, 1998). The current model adopts a modified extended self-theory to explain the human-computer relationship. It does this by describing the acts and functions that a technology enables us to do. To elaborate, an affordance *"refers to the physical requirements for an action"* (Adolph, 1995, p. 734). Therefore, technology executes actions by having affordances or features that extend a person's capabilities, possessions, and environment. This can allow a person to achieve something which wasn't previously possible without the technological intervention or can improve previous methods. When designing or evaluating a technology people should consider four broad categories of extension (see Table 2.3). It is proposed that technology extends and adds affordances to our mind, body, environment, and possessions.

However, it is also important to consider when technology can impede or become a negative influence. Belk (1998) considers how a loss of possessions can have a negative impact on a person's sense of self. Dependant on the unique features of a technology, a feature might block successful technological extension, or even remove affordances from the user. In extreme cases, some features make the benefits of using a technology obsolete and discourage use. For example, early optical character recognition systems were inaccurate in comparison to human reading abilities at recognising words in text (Govindan & Shivaprasad 1990).

Table 2.3. Descriptions and examples of how technology can extend and subtract from a person's mind, body, environment, and possessions.

Extension Category	Extension	Subtraction
Mind	Technology may 'think' for its user i.e. when using a calculator to compute sums, freeing cognitive resources for other tasks. Technology can extend our mental abilities (Clark & Chalmers, 1998); for example, using your smartphone to remind you of certain events can help aid natural memory capabilities. Imagine visualising several ideas in your head verse drawing out your ideas in a mind map on a whiteboard. Both achieve the cognition of formulating ideas but use different mediums. A person's psychology, i.e. personality and sense of self can also be extended with technology (Belk, 1998).	A technology will not extend its user if it is too difficult to utilise its affordances. Problem solving due to a technology being difficult to use would impose a heavy cognitive load on the user (Sweller, 1988). Smartphone notifications have been shown to interrupt a task and be disruptive (Bowman, Waite, & Levine, 2015) and peoples' working memory capacities, are related to their ability to multitask (Pollard & Courage, 2017). It has also been argued that offloading thinking onto smart devices causes a new type of cognitive laziness and users may lose the ability to think for themselves (Barr et al., 2015).
Body	There are two types of human-technology bodily amalgamation; technological incorporation (e.g., prosthesis) and technological extension (e.g., tool use) (de Preester & Tsakiris, 2009). Technological prosthesis can be incorporated into our neuronal body-model that represents the anatomical features of a normative body (de Preester & Tsakiris, 2009). The majority of technology fits into the second category and are considered tools that can extend the human organism and lived body (Steinert, 2015). Tools and objects can extend us by extending our body schema (Iriki et al., 1996).	A technology that is too physically demanding or difficult to use will prevent that technology from extending the person and may even subtract from their physical abilities when performing other tasks if all efforts are directed to using the technology. Power tools can cause limb injuries (Ku, Radwin, & Karsh, 2007) and smartphones, tablets and laptops which encourage unnatural upper body movements have been associated with an increase in repetitive strain injury (Christopherson, 2015).
Environment	Technology can provide new environments for a person to percieve and interact. Social networking sites and virtual reality are considered digital environments. Transport can enable you to go to a new location. Technology can provide new aesthetic and sensory stimulation. The mind is an internal environment and technology can create new environments through mental escapism and flow (e.g., when listening to an audiobook) (Calleja, 2010; Csikszentmihalyi, 1990; Kuo, Lutz, & Hiler, 2016).	Technology can damage and reduce the environment by polluting the air and the sky (Colvile, et al. 2001; Falchi, et al. 2011; Sohaili, 2010). Communication in an instant messaging environment satisfies basic social needs less than face to face interactions (Sacco & Ismail, 2014). A product which is un-attractive to the visual, haptic, and olfactory senses is likely to discourage use. Different types of environments such as private spaces may be reduced due to advances in technology.
Possessions	When a person receives a piece of technology, whether it be hardware, software or item collecting in games, it gets added to a persons collection. Possession extension concerns how your possesions work together, i.e. a new technology can improve what you currently own. A new technology may also replace a system if it has better affordances than a previous version. Possessions also have monatory value, and thus extend a persons abstract possessions such as wealth.	Obtaining a technology often subtracts from a person's wealth. New technology can also be incompatible with the technology that is already owned. This can lead to a subtraction in affordances if the combination of the two technologies prevents either one from executing its affordances. An example would be incompatible hardware and software. Technology may execute affordances that removes something from a person's possessions completely i.e. computer viruses.

2.3.3.5. Intrinsic and Extrinsic Motivations

The current model argues that people use technology to satisfy both intrinsic and extrinsic motivations. Some motivations are short lived (e.g., complete a singular task), others are ongoing and require maintenance (e.g., the desire to be part of a social group). Thus, people will maintain several motivations simultaneously, but with different levels of saliency. Examples of using a technology for extrinsic purposes include using a technology to manage money, preserve the environment or to improve physical health. Therefore, extrinsic motivations are goal oriented and instrumental (Wu & Lu, 2013). In contrast, intrinsic motivations are described as using a technology because of the desire to have a particular internal human experience such as, joy, pleasure, fear, satisfaction, excitement, or pride (Lowry, Gaskin, Twyman, Hammer & Roberts, 2013). Perceived enjoyment has been shown to increase intentions to adopt an online payment system and has also been shown to be a strong predictor of intended continual use of Habbo Hotel - a virtual, social world (Rouibah, Lowry, & Hwang, 2016; Mäntymäki & Salo, 2011). Accepting that intrinsic motivations play a role in technology adoption and use, the decision to use a technology does not always have to be rational, i.e. when using gambling machines to satisfy feelings of addiction (Gainsbury, King, Russell, Delfabbro, & Hing, 2017). When contemplating reasons for the low retention rates of wearable technologies, it has been proposed that *"many wearables suffer from being a solution in search of a problem"* and *"don't add functional value"* (Piwek, Ellis, Andrews & Joinson, 2016, p. 2). As such, the designed purpose of a technology must therefore satisfy or be perceived to satisfy at least one of the users intrinsic or extrinsic motivations if a developer wants to encourage use.

These intrinsic and extrinsic motivations can also include social factors such as subjective norms, image, and social influence which are common across technology use models (Venkatesh & Davis, 2000; Venkatesh, Morris, Davis & Davis, 2003; Venkatesh & Bala, 2008; Kim & Crowston, 2011; Venkatesh, Thong & Xu, 2012). They collectively refer to a user's perceptions of how others view them if they were to use the technology. However, social factors do not have to be considered separately from a person's motivations. Workman (2014) describes in a literature review how humans have a need for experiencing relatedness, which is the need of belonging and being connected with others. The need to belong has been proposed to explain why people use social media such as Facebook (Nadkarni & Hofmann, 2012). Workman (2014) further explains that when technology satisfies this need, a person's intrinsic motivation to use that technology may increase and encourage them to use this further. As a result, social factors appear to be an influential mechanism when understanding the continued use of a technology, however, this does not require a separate construct from other types of human motivation.

2.3.3.6. Cost Benefit Decision

Existing technology use models posit that behaviour is consciously driven from beliefs, attitudes, and other evaluative assessments such as 'performance expectancy' (Venkatesh, Morris, Davis & Davis, 2003). More recently, 'value-based' research models have been applied to technology use, whereby the variable, 'perceived value' examines the utility of technology, based on trade-offs between the perceived benefits and costs (Setterstrom, Pearson & Orwig, 2013) and has been shown to be predictive of intention to use (Hong, Lin & Hsieh, 2017; Cocosila & Igonor, 2015). Measuring people's cost-benefit decisions are advantageous because the outcome of this assessment is a choice to use the technology or not and is conceptually more of a direct precursor to technology use than 'behavioural intention'. Setterstrom, Pearson & Orwig (2013, p .1143) stated that *"perceived value increases as either the benefits from product consumption increase or the costs associated with consumption decrease"*. Therefore, perceived value has enhanced empirical falsifiability when compared to related constructs such as attitudes, as the formation and structure of attitudes are still being explored and debated in the literature (Hogg & Vaughen, 2008). Consequently, the most effective method of capturing a person's opinion of the technology, prior to use, is through their assessment of costs and benefits, and the consequence of this decision is immediately observable through either use, or no use of the technology.

In TIM, the process of technology extension and subtraction is an interplay between how a technology adds and removes affordances from its user. However, whether it is perceived to cost or benefit the user will depend on whether this extension/subtraction is in line with a person's motivations. A technology will be perceived to benefit its user if its features increase the ability for a person to satisfy their motivations. A technology will be perceived to cost the user if its features deduct from the ability to satisfy their motivations. As technologies will most likely have both additive and subtractive features, the user will weigh up whether the technology is worth using. Overall the outcome of this decision-making process is binary (worth or not worth using in that instant), and if positive will prompt use.

2.3.3.7. Situational Context

When the decision to use a technology becomes less conscious, use can also be prompted by contextual cues such as location, existing routine, events, objects, or proceeding actions (Stawarz, Cox & Blandford, 2015). Contextual factors such as being in a hurry or long queues have been shown to have a direct positive effect on intention to use a mobile ticketing application (Mallat, Rossi, Tuuanainen & Öörni, 2009). Time of day is also related to a user's frequency of smartphone use (Andrews, Ellis, Shaw, Piwek, 2015). The term context, however, is ambiguous and can refer to a diverse range of meanings. Venkatesh, Thong & Xu (2016) describe 4 variables which could be considered contextual constructs. The first 'environmental attributes' denotes the lights, temperature and the immediate physical environment around a person when using technology. They also describe 'location attributes' such as culture, regional economy and organisational competition. Events (time) can be considered a contextual variable as it signifies the temporal setting. Finally, 'organization attributes' can also belong to this context theme, as it includes climate, organizational culture, leadership, and collective technology use (Venkatesh, Thong & Xu, 2016).

Due to the scope of the current theory, situational context is defined as the immediate environment surrounding the person directly prior to using a technology. This definition is similar to 'environmental attributes', and includes the objects, people and current events that are part of the user's immediate surroundings. However, our adaption also incorporates the place and time as these can reflect a user's routine and habit, which are important predictors of technology use, and are informative when describing the 'present moment' (Stawarz, Cox & Blandford, 2015). Place reflects a user's GPS location which can provide details as to where the technology is being used (e.g., the country, city, or building) and other meaningful locations, such as whether the user is at home or work. Time reflects temporal attributes such as time of day and day of the week etc. As a result, this new construct is termed situational context. It does not include social groups, organizations, or societal attributes to which a user belongs due to the scope of the theory. Although, existing and future sociological theories such as the diffusion of innovation model may find these useful to describe when understanding how technology spreads (Rogers, 2003). Related concepts can be examined when measuring individual differences such as culture or occupation. By defining and reducing context to what is described above, we can ensure that situational context has practical value in subsequent research.

2.3.3.8. Technology Use

It is common across models to include a variable that represents the use of a technology (Davis, Bagozzi & Warshaw 1989; Venkatesh & Davis, 2000; Limayem, Cheung & Chan, 2003; Kim & Malhotra, 2005; Venkatesh, Thong & Xu, 2012; Venkatesh, Thong & Xu, 2016). Very few designs have successfully measured objective usage (Turner et al., 2010; see chapter 4). Instead, activity is predominately measured subjectively via self-reports methods as a substitute for actual logs of technology use (Shaikh & Karjaluoto, 2015; Taylor & Todd, 1995; Turner, et al. 2010). Furthermore, behavioural intention is a variable often included in models (Davis, Bagozzi & Warshaw 1989; Bhattacherjee, 2001; Limayem, Cheung & Chan, 2003; Kim & Malhotra, 2005; Venkatesh, Thong & Xu, 2012; Venkatesh, Thong & Xu, 2016) because it has been *"posited by many theorists as the closest cognitive* *antecedent to actual behaviour"* (Setterstrom, Pearson & Orwig , 2013, p. 1141), and avoids issues with developing applications that can measure technology use such as programming barriers, consent form "blindness" and privacy/security issues (Piwek, Ellis & Andrews, 2016). However, in a review of 73 publications, the predictor variables in TAM were shown to be better at predicting behavioural intention than actual usage (Turner et al., 2010). Although challenging, attempts should be made to measure actual usage, through computer science collaborations or through the use of programming frameworks (Piwek, Ellis & Andrews, 2016; see chapter 4). To encourage this direction and to promote parsimony, it is unnecessary to include in a model a substitute variable alongside a construct which represents actual technology use. Thus, the general theme of 'technology use' is deemed more appropriate for future models as it concerns itself with actual use.

The first and most straightforward technology use measure that could be explored relates to a person's choice. Does a person choose to use a new system/technology, or do they continue to use the systems and technology they already have? An additional measure involves collecting objective usage over time via the technology itself (see chapters four, five and six). There is the assumption that increased use is indicative of greater levels of technological integration. However, it is proposed here that consistent patterns of use may be more symptomatic of successful technological integration than a sum of overall use. For example, do you use your phone alarm to wake you up every morning? Thus, is a technology used again when aiming to satisfy the same motivations, or used repeatedly in the same contexts? This highlights that continued technology use needs to be measured longitudinally to investigate how new habits and new patterns of technology use arise (see chapter five). It is also important to understand that there are often distinctive layers to any technology. Generalised mobile phone use for example, can be measured directly as a whole, or the use of a specific application can be quantified specifically. However, by defining exactly the technology which is to be measured, it is easier to develop applications and data logging platforms which can quantify the use of the technology under investigation. This will aid the unnecessary collection of data beyond the scope of the project, making analysis simpler, as data logging itself produces a large quantity of valuable data (see chapters four and five). It is also more ethical to only collect data on the specific usage behaviours of interest.

2.4. Discussion

2.4.1. Theoretical Contributions

TIM was developed in response to an absence of theory in the field of Cyberpsychology (Orben, 2018), and due to a lack of understanding of 'everyday' and 'none-pathological' technology use. Through unifying existing theories with a psychological lens, the field has gained testable hypothesis when it comes to technology use behaviours. For example, TIM predicts that a technology will be used long-term if it repeatedly satisfies a user's intrinsic and extrinsic motivations. TIM also predicts that if a technology continually extends a person's affordances, then the user will consider the technology worth using across time. TIM further predicts that two variables, situational context and real-time decision making are direct precursors of technology use. Finally, it is considered why people use technology in the first instance. Technology often extends the acts and functions of a person when trying to satisfy a user's intrinsic and extrinsic motivations. Therefore, the theoretical development in chapter two has successfully created a framework which can increase our understanding of 'everyday' technology use.

Technology can have both positive and negative effects on the user and TIM extends the current knowledge base by proving a number of testable relationships that are likely to underpin this phenomenon. The inclusion of a new variable, Technology Extension and Subtraction, alongside how this interacts with intrinsic and extrinsic motivations during decision making, explains why a person uses a technology despite potential negative effects. For example, if the user goes through a cost-benefit decision making process, whereby a technology helps satisfy a salient intrinsic motivation, such as an addiction, this might outweigh the costs associated with using the technology. Thus, the use of a technology does not have to be rational. Therefore, TIM escapes the limitations of existing theories by considering the convoluted relationship between technology use and the impact it has on the end user. This was achieved by capturing the core human-technology relationship through advancing extended-self ideas (Belk, 1988).

Theories of technology use often state that habit is an important influence of use (Limayem, Cheung & Chan, 2003; Setterstrom, Pearson & Orwig, 2013; Kim & Crowston 2011; Venkatesh, Thong & Xu, 2012; Venkatesh, Thong & Xu, 2016). TIM also extends existing theoretical knowledge here by illustrating how habitual use may form. As the model iterates with every use, we can measure the proposition that situational context will become more predictive and the cost/benefit decision will become less predictive of technology use over time. The more a technology is used in response to situational cues, rather than conscious decision making, the more habitual a technology has become (Stawarz, Cox & Blandford, 2015).

Furthermore, individual differences are described in the model as a precursor of technology use. Therefore, it is possible to track through the model how individual differences would be indicative of usage behaviours. Specifically, TIM predicts that individual differences effect whether a technology would add or remove affordances from a person during technological extension or subtraction. For example, using an electronic hearing aid would not extend the affordances of someone with 'normal' hearing, but would add to the abilities of someone with hearing loss. The result of this evaluation would affect whether a technology was considered worth using or not and finally would influence subsequent technology usage behaviours. With relevance to personality prediction, TIM and Belk's extension-of-self theory (Belk, 1998, 2013) describe how technology can extend a person's mind, as whenever a person uses a technology, the choices and personalisation they make (e.g., deciding what music to play on Spotify) extends their characteristics into their technology use patterns. Furthermore, TIM and extension-of-self theory describe how greater agency over their technology provides greater opportunity for personalisation, and thus, greater extension (Belk, 1988, 2013). Therefore, TIM predicts that digital traces with greater variability (e.g., application usage behaviours vs operating system choice) would lead to better personality predictions.

Furthermore, demographics and individual differences, may influence a person's intrinsic and extrinsic motivations when using that technology. For example, a person who is unemployed may use a computer to apply for work, whereby a child may use a computer for educational and entertainment purposes. Consequently, people with different personalities and demographics may use technology for different reasons, when extending their affordances to satisfy these motivations. These 'human factors' may be reflective in their choice and patterns of technology usage and is explored further in chapter's three and five of this thesis.

2.4.2. Applied Impact

Understanding and predicting continued technology use requires interdisciplinary collaboration (Schulz et al. 2012). TIM encourages interdisciplinary research because designing effective features of technology requires expertise from engineering, creative arts, cognitive and computer scientists. Equally, understanding individual differences, motivations and decision making requires expertise from medicine, psychology, and the social sciences more broadly. Measuring situational context may benefit from geographical science knowledge, and many other disciplines could provide novel ways to examine the relationships and variables in TIM. The interdisciplinary focus of TIM can prompt several new avenues of research and will hopefully allow the field to develop more quickly. Thus, TIM has the potential to be highly generative.

Through describing how the model repeats, TIM encourages longitudinal research through the long-term tracking of each variable, which is arguably fundamental in the study of continued technology use. A collaboration between social and computer scientists could promote methods which document usage directly through logging technology (see chapter four). Researchers could also further utilise methods derived from ecological momentary and ambulatory assessment to examine other variables such as context, individual differences, and motivations. These methods study individuals in their natural setting, in real time by using smartphones and wearable technology to sample a person's current mood, heartrate, location and other streams of data via several snapshots over time (Conner & Mehl, 2015) (see chapter six). Studying relationships in ecological settings with direct measures ensures that results from subsequent research is closer to ground truth.

By looping the model iteratively, factors which lead to technological abandonment or long-term integration can be repeatedly measured using this methodology. For example, are the features of a technology the same, worse, or improved? Is the technology still extending the person or has a person's motivation changed? Finally, is the user still residing in contexts that allows them to use the technology? All these points may predict why a technology stops being used. In practice, if following ecological momentary and ambulatory assessment methodologies, it is assumed that the same tools and measures of individual differences, situational context, technological features, technology extension and subtraction, intrinsic and extrinsic motivations, agency, cost/benefit decision and technology use will be used repeatedly after a pre-defined length of time has passed since the last iteration. Therefore, TIM can be used to underpin longitudinal research.

The Technology Integration Model provides a tool for stakeholders to use with the purpose of aiding business practices, consumer satisfaction, technological design, and other applications. TIM can be used by professionals in many occupations. Designers should seek to develop and refine technology which extends a person's mind, body, environment, and possessions whilst minimising subtraction that will discourage use and have a negative impact on the user. Technology should be designed with the users' motivations in mind, whilst aiming to maximise the compatibility between technological features and the user. It may be possible for a consumer to pick a technology that is most suited to them. For example, when choosing a smartphone, it is possible that a person's individual differences will predict whether they should ideally purchase a smartphone with specific features (see chapter three). TIM moves the focus onto how technology can benefits consumers, and as a result technology developers and companies are assisted when creating technology that positively impacts the end user. As TIM explains technology integration beyond adoption and predicts future use, developers can use these predictions to produce satisfying and beneficial products for the user.

TIM describes how a technology might become a part of someone's everyday life, making it stand out from other theories created by researchers from an information systems or business management perspective (Venkatesh, Morris, Davis & Davis, 2003; Kim & Crowston, 2011; Davis, Bagozzi & Warshaw 1989; Bhattacherjee, 2001). However, its predictions can still be applied within occupational and educational settings. When implementing new systems in the workplace, consider employees perception of agency. If this is perceived to be low, companies can provide interventions such as training and practice sessions. In addition, management should ensure that a change in system will extend the employees possessions beyond the systems that are currently in place if they wish to encourage use. Whilst use of a new technology is largely mandatory in work environments, the integration process could be made more efficient and effective if the employees themselves view the technology as worth using even if it was optional. This may encourage more spontaneous use of the technology, as without the perception of a technology being worth using, it is likely that employees will use the technology to the minimum, rather than exploring a technology's full potential.

2.4.3. Limitations

While the model is derived from recent empirical work, and took inspiration from existing theories, future research is now required to empirically document or critique the relationships that have been defined. This will involve key decisions regarding how each aspect can be best measured. TAM is often relied on due to is its validated inventory of psychometric measurement scales (Yousafzai et al., 2007a). Moving forward, TIM will require its own standardised set of validated empirical methods and measures if it is to be effectively operationalised by other researchers. Notably, chapter three describes how technology 'choice' can be measured through an assessment of smartphone brand ownership. Chapter four focuses on how to measure technology use objectively, through logging applications. Therefore, the rest of the thesis starts with an exploration of the last variable in the model, 'technology use', which is arguably the most salient variable to address when operationalising TIM.

Ultimately, the purpose of creating theories is to simplify the phenomena under investigation and allow for improved understanding. However, this requires a careful balance. Existing unification models have a multitude of constructs and a convoluted web of moderating and mediating variables (Venkatesh, Thong & Xu, 2012;

Venkatesh, Thong & Xu, 2016). Due to their lack of usability, researchers rarely adopt these unification models. On the other hand, traditional models like the TAM oversimplify the complex relationships between technology use and people. Such models lack the ability to generate new knowledge that can change subsequent engagement with technology (Davis, Bagozzi & Warshaw 1989). During the development of TIM, it was deemed important to continue refining the identified key themes. TIM subsequently only developed constructs within a defined scope to limit the number of variables included in the final model. However, TIM takes inspiration from many disciplines to ensure thorough explanation of the chosen phenomenon, which focuses on an individual's technology use. Thus, one of the contributions of TIM is a balance of explanatory value and parsimony.

Like the TAM, it is unlikely that all the relationships and concepts in TIM will be tested simultaneously (Yousafzai, Foxall, & Pallister, 2007a). However, TIM can be broken into sections. For example, a researcher can measure what predicts technology extension or subtraction, the cost-benefit decision or technology use, as the variables which predict each of these constructs are shown in Figure 1. It can also be critiqued that variables such as individual differences, intrinsic and extrinsic motivations and technological features in TIM are broad in nature. However, it remains important that the described concepts in TIM are general enough for a wide range of technologies so that researchers do not need to test specific hypothesis for each study. It is possible to test idea that individual differences and technological features predict technological extension or subtraction, irrespective of which individual difference or technological feature under investigation. Equally, one can test the hypothesis that motivation influences the decision-making process by using a combination of different motivations. These features ensure that TIM will remain relevant as new technologies emerge.

2.4.4. Conclusions

TIM is a new model which predicts continued technology use and provides strong explanatory value whist maintaining parsimony and practicality. Each loop in TIM represents one use and this iteration is necessary as human-technology integration may not occur instantly but develop over time. This can be measured by examining the individual contributions of conscious decision-making alongside automatic use in response to contextual cues across several iterations of the model. The model is generative, and can inspire a multitude of hypothesis driven research, largely due to the new relationships and concepts described. TIM promotes the development of technology that includes extending features, which satisfies a user's motivations, particularly if aimed to be used long-term. As a result, the model can be applied to a broad range of contexts, being able to adequately explain the use of existing and future technology. It encourages interdisciplinary collaborations and the exploration of new and objective research methods. In sum, TIM can hasten progress and generate new knowledge in the ever growing and important field of continued technology use.

In the next chapter, we apply conceptualisations regarding how individual differences influence technology use to understand the reverse; if a person's choice of technology is indicative of their personality and demographics. Rather than assessing people's intentions to use specific devices, chapter three directly assesses ownership, whether a person has chosen to use an iPhone or an Android smartphone.

Chapter 3

Smartphone OS and the Extended-Self

The following chapter forms part of the publication: Shaw, H., Ellis, D. A., Kendrick, L-R., Ziegler, F. V., & Wiseman, R. (2016). Predicting smartphone operating system from personality and individual differences. *Cyberpsychology, Behavior, and Social Networking, 19,* 727-732. doi:10.1089/cyber.2016.0324

3.1. Introduction

The Technology Integration Model outlined in Chapter 2 describes how digital traces of behaviour can be used to infer information about the user. This is because, individual differences are important for predicting technology usage patterns, and as a consequence, a person reveals parts of their characteristics in the way they use their technology. For example, previous research has found a positive association between the number of phone-calls a person makes per day and extraversion (Montag et al. 2014). In addition, sociodemographics and personality have been predicted from smartphone application use (Kim, Briley & Ocepek, 2015; Chittaranjan, Blom & Gatica-Perez, 2013; Stachl et al. 2017). However, this chapter aims to explore whether a person's choice to use a specific technology or not, outlined in Chapter 2, has the potential to reveal information about the user. For example, watch wearing has been shown to be a marker for conscientiousness (Ellis & Jenkins, 2015) and Windows users are on average older than Mac OS users (Götz, Stieger & Reips, 2017). Electric car owners are younger and have higher income and education than conventional car owners (Simsekoglu, 2018). Thus, it may be possible that there are differences between the two largest groups of smartphone owners, Android and iPhone users, which have a 50/50 split in the market share in the U.K. (Statista, 2018).

Exploring whether a person's smartphone operating system can provide information about the user has practical implications, because it is arguably the simplest digital trace that can be collected from a user. When considering targeted advertising or when software aims to personalise user experience, the less information collected about the user, the smaller the impact on user privacy (Seneviratne et al. 2014). Therefore, this research may show how little data is needed to adequately predict consumer traits and preferences.

In addition, there has been increase in smartphone-based research methods across many disciplines that collect data via smartphone applications (Götz, Stieger & Reips, 2017). There are many benefits to this method including: reaching a wider demographic of participants, ease of data collection, and higher ecological validity (Miller, 2012). However, due to technical barriers in these methods, researchers often create applications for a singular smartphone operating system (Piwek, Ellis & Andrews, 2016; Götz, Stieger & Reips, 2017). This may be problematic if users of one smartphone operating system differ in their personality and demographics from others, questioning generalisability across samples. Therefore, when using these new data collection methods, it is important to understand if there are any limitations due to differences between iPhone and Android users.

In addition to the Technology Integration Model (TIM), there are several none technology related theories which explain why smartphone use may be informative of a user's personality traits and demographics (Aaker, 1997; Adam & Galinsky, 2012; Belk, 2013). It is postulated that consumers anthropomorphise brands whereby brands themselves have perceived personalities (Aaker, 1997). When consumers make a purchase choice, it has been posited that they choose a brand that is either congruent with their ideal or actual self-identity (Koo, Cho & Kim, 2014; Hosany & Martin, 2012). If consumers choose a brand in order to become more like their ideal self, then they may 'embody' the semantics attached to that brand, creating similarities between the products they own and themselves (Adam & Galinsky, 2012). Alternatively, if customers choose a product that is congruent with their actual self, it can be argued that the technology extends their current self-identity (Belk, 1998). Belk's extension of self-theory suggests we place part of our self-identity in the technology we use due to the way we personalise and manipulate it (Belk, 2013). The more power and control a person has over the technology, the more it will extend them (McClelland, 1951; Belk, 1998). Choosing a smartphone brand is arguably the first type of smartphone personalisation a user can control. Therefore, extension-of-self theory, embodied cognition and TIM describe how the user amalgamates with the products that they acquire, demonstrating how user information can be extrapolated from the technology they own.

Smartphones are ubiquitous devices, with the main brands (iPhone and Android) engaging in extensive advertising campaigns, including the unveiling of new products during keynote presentations (Mickalowski, Mickelson, & Keltgen, 2008). Their brand personality is projected through these advertising campaigns, providing new information which can be incorporated into the social representation of each brand (Höijer, 2011). Apple promote their products as having a particular status amongst the mobile market, e.g., *"If it's not an iPhone, it's not an iPhone"* (Miller, 2015). In contrast, Android promote their operating system as a way to be none conforming yet collective e.g., *"Be Together. Not the Same"* (Li, 2016). Therefore, it is possible to examine if the brand personalities projected by adverts is congruent with the personalities of iPhone and Android users respectively.

In addition to exploring the congruence of brand personalities, psychological trait perspectives describe how people's personalities can be summarised through their locus on five or six core traits (Fleeson & Jayawickreme, 2015). When used to create personality tests, these assessments are an insightful way to examine differences and similarities between people because they subsequently have been used to predict a persons' behaviour in specific situations (Fleeson & Jayawickreme, 2015). For example, an individual's level of agreeableness has been found to predict the frequency and number of hours they will spend on mobile phone games (Seok & DaCosta, 2015). However, there is minimal research to this date which explores whether personality differences occur between iPhone or Android users.

The exact taxonomy of personality traits is still heavily debated in the literature, but largely a 5-factor solution, called the 'Big-5' is accepted. (Maltby, Day, & Macaskill, 2010). Many models of personality including the 'Big-5' adopt the lexical hypothesis, which states that the major dimensions of personality are the most salient characteristics encoded in language (Anglim & O'Connor, 2019). As a consequence, it is possible that the number of traits derived from personality research can be biased by only studying the English language, which is a major criticism of the 'Big-5' approach (Anglim & O'Connor, 2019). However, recent factor analysis research across several languages has suggested that six (rather than five) core personality characteristics exist and these are honesty-humility, emotionality, extraversion, agreeableness, conscientiousness, and openness-to-experience (HEXACO) (Ashton, Lee, & de Vries, 2014). The HEXACO model separates the traits ‘neuroticism’ and ‘agreeableness’ from the ‘Big-5’ into three separate traits ‘agreeableness’, ‘emotionality’, and ‘honesty-humility’ (Anglim & O’Connor, 2019). Measuring the sixth trait, ‘honesty-humility’ is considered one of the strengths of the HEXACO taxonomy of personality, as it allows researchers to assess morally relevant behaviours (Anglim & O’Connor, 2019). As discussed in chapter one, by adopting this ‘nomothetic approach’, the benefits of studying common traits include the ability to make direct comparisons between people, e.g., iPhone vs Android owners. For the reasons outlined above, this chapter measures personality using the HEXACO model.

Furthermore, if personality differences exist between iPhone and Android users, this may lead to stereotype formation whereby particular characteristics are associated with users of each brand. Stereotypes are frequently described as *“the typical picture that comes to mind when thinking about a particular social group”* (Dovidio, Hewstone, Glick & Esses, 2010, p.7). Stereotypes concerning iPhone and Android users could be formed through an evaluative process called ‘Anchoring’, described in Social Representations Theory (Augoustinos, Walker, & Donaghue, 2009; Moscovici, 1984). People typically compare a new object or a group of people to those that they already know, and as a result, evaluative ideas are formed about the new thing or group. If brands are socially constructed through media, it is possible that stereotypes may also be constructed about the users of different smartphone brands (Höijer, 2011).

Stereotypes concerning how groups differ in personality traits have previously been documented. For example, single people are perceived to have less positive personality traits than coupled equivalents, children without siblings to be more spoiled and selfish than those with siblings, and people who wear glasses are perceived to be more intellectual and conscientious than those who do not wear glasses (Borkenau, 1991; Greitemeyer, 2009; Hellström & Tekle, 1994; Mõttus, Indus, & Allik, 2008). It is therefore possible that people divide iPhone and Android users into two unique groups and consequently form distinctive social representations about their personality. This is important to consider for two reasons. Undesirable stereotypes may negatively affect those who use this technology (Kaye & Pennington, 2016). Secondly, if people cannot accurately judge the personality of those in specific groups, then it is possible that computer algorithms might replace the need for observer reports in personality research (Hinds & Joinson, 2019; YouYou, Kosinski & Stillwell, 2015).

Research comparing iPhone and Android owners to date is minimal, with studies largely exploring demographic differences (Smith, 2013; Hixon, 2014; Bjelland et al. 2012). These studies suggest that iPhone users have higher economic status than Android users (Smith, 2013; Hixon, 2014). This has some empirical support as Götz, Stieger and Reips (2017) found using an online survey of over 1000 smartphone users that iPhone owners were wealthier than Android owners. In addition, they also found that Android users score higher on the personality trait openness when using a 20-item measure of the 'Big 5'. However, effect sizes in this study were small (Götz, Stieger & Reips, 2017). Another study found that iPhone users have more social relationships and cluster around city centres, whereas Android owners dominate rural areas. (Bjelland et al. 2012). Therefore, prior work suggests that iPhone users may have greater financial resources and higher sociability than Android users. Based on the theoretical review and findings from previous research, several hypotheses were explored:

Hypothesis 1: *iPhone users will score higher on HEXACO 'extraversion' measures than Android Users.*

Hypothesis 2: *iPhone users will self-report higher socio-economic status than Android users.*

Hypothesis 3: *In line with the current advertising campaigns of each brand, iPhone users will see their smartphone as more of a status object and will avoid similarity less than Android users.*

Hypothesis 4: *iPhone users will have the stereotype of being more social than Android users.*

The proposed hypotheses were explored across two studies. In study one, an online survey was created to assess individual differences between iPhone and Android users via several self-report scales. In study two, surveys were conducted in person around the university campus to assess whether there were stereotyped differences between iPhone and Android users.

When analysing data collected from personality tests and questionnaires, this chapter combines null hypothesis significant testing (NHST) with predictive modelling more commonly used in data science disciplines. For example, classification algorithms (aka classifiers) are a form of 'supervised' machine learning which examine how predictor variables can be used to classify people into pre-defined groups (e.g., iPhone vs. Android users) (Bali et al. 2016, page 45). By combining the two perspectives, NHST can help confirm hypotheses, and classification models can then use these insights to reliably predict future behaviours (e.g., ownership). Take, for example, binary logistic regression modelling which spans both approaches. By examining if each variable included in the model significantly predicts the criterion variable, it is possible to falsify that certain variables are related to smartphone ownership. Consequently, as a data reduction method, only variables which receive empirical support are carried forward in predictive models. Furthermore, binary logistic regression models produce *B* coefficients. These describe precisely how each variable contributes the classification of either an iPhone or Android user. Subsequently, *B* coefficients can be used to predict who owns which brand in future samples based on their personality traits and demographics (see section 3.2.2.6.).

Binary logistic regression models are just one of many classification algorithms that are frequently adopted across analogous data science disciplines. Decision tree algorithms can be used to transparently visualise how people get classified into particular groups based on input variables (see Fig 3.4). Decision trees do not assume that the contribution of each predictor variable has a linear association with the criterion variable and can therefore, be used to model variables which violate normality assumptions (Merkle & Shaffer, 2011). Finally, aggregate approaches such as random forests, which combine the predictions of many decision tree models, have increased predictive generalisability to future samples (Breiman, 2001). Thus, by adopting a combined approach, the predictive validity of significant variables is verified on unseen/new data, through using data science techniques, heightening reliability. However, by using hypothesis testing approaches, it is possible to increase the probability that the variables chosen to train classifiers will actually predict ownership.

3.2. Study One: Individual Differences Predict Smartphone OS

3.2.1 Methods

3.2.1.1. Measures

To investigate differences between iPhone and Android users, participants completed an online survey containing several psychometric tests:

Personality

The 60-item HEXACO was administered to measure personality differences between the smartphone user types across six domain level traits; honesty-humility, emotionality, extraversion, agreeableness, conscientiousness, and openness-to-experience (see Table 3.1.) (Ashton & Lee, 2009). For each trait, ten questions were answered concerning how much a participant agreed or disagreed with a statement about themselves. Answers were recorded on a five-point Likert-style scale, whereby five = strongly agree and one = strongly disagree. The HEXACO-60 is the shorter version of the HEXACO-PI-R and thus was more suited for time-constrained survey research (Ashton & Lee, 2009).

Table 3.1. A list of the six HEXACO traits alongside adjectives of people who score high in each trait (Lee & Ashton, 2008)

Personality Trait	Related Adjectives
Extraversion	Outgoing, Social, Lively, Vibrant, Extroverted, Talkative, Sociable Chatty, Cheerful, Bubbly, Vocal, Confident, Happy-go-lucky Energetic.
Conscientiousness	Organized, Thorough, Hard-working, Efficient, Self-disciplined, Careful, Tidy, Proper, Diligent, Studious, Meticulous, Responsible, Mature, Perfectionistic.
Honesty-Humility	Sincere, Honest, Trustworthy, Giving, Kind, Warm-hearted, Humble, Helpful, Loyal, Compassionate, Good-hearted, Modest, Kind-hearted Big-hearted.
Agreeableness	Agreeable, Calm, Peaceful, Patient, Cooperative, Mild, Relaxed, Tolerant, Forgiving, Lenient, Easygoing, Pleasant, Gentle, Passive.
Emotionality	Emotional, Feminine, Sensitive, Sentimental, Oversensitive, Nervous, Whiny, Fearful, Melodramatic, Anxious, Gullible, Moody, Nagging Clingy.
Openness to experience	Philosophical, Insightful, Complex, Deep, Introspective, Articulate, Inquisitive, Unconventional, Perceptive, Analytical, Individualistic, Intuitive, Intellectual, Imaginative.

Social Economic Status

A measure of *Social Economic Status* (SES) was included in the online study. To avoid subject attrition through making the participants feel uncomfortable, we did not ask participants to state their annual household income. Instead, we used the MacArthur ladder of subjective social status to measure a person's perceived social economic status in society (Adler, Epel, Castellazzo, & Ickovics, 2000). In this scale, participants viewed a picture of a ten-step ladder. The instructions were: *"There are 10 steps on this ladder. At the top of the ladder are the people who are the best off, those who have the most money, most education, and best jobs. At the bottom are the people who are the worst off, those who have the least money, least education, and worst jobs or no job. On the multiple-choice options below, please select a step which best represents where you stand on this ladder"*. Through using the MacArthur ladder of subjective social status, it was possible to measure whether one smartphone user group was higher in perceived Social Economic Status (SES) than the other.

Attitudes Towards the Mobile Phone as a Status Object

A scale which measured 'Attitudes Towards the Mobile Phone as a Status Object' (ASO) was included in the online study. This scale comprised of six statements that were taken from Vanden & Roe (2013) such as *"It is cool to have a cool phone"*. Participants were then required to respond to these statements on a four-point scale ranging from *"completely disagree"* to *"completely agree"*. At the time of data collection, Apple's television advertising motto for the iPhone was *"If it's not an iPhone, it's not an iPhone"* (Miller, 2015). The ASO scale therefore coincided with the theme of the iPhones adverting campaign. As a result, it was of interest to investigate if Apple iPhone users scored higher on this scale than Android Phone users.

Avoidance of Similarity

To coincide with the ASO, the advertising motto for Android Smartphone's was also investigated. At the time of data collection, Android's television advertising motto for their smartphones was *"Be Together. Not the Same"* (Li, 2016). Therefore, a scale which measured 'Avoidance of Similarity' (AS) was included in the online study. The AS scale was derived from a subscale within Ruvio, Shoham, & Brencic's (2008) 'Consumers need for uniqueness' scale, which directly tapped into brand and product ownership preferences. The AS comprised of four statements such as *"I often try to avoid products or brands that I know are bought by the general population"*. Participants responded to these statements on a five-point scale which ranged from *'Strongly agree'* to *'Strongly disagree'*. It was predicted that Android Phone users would score higher on this scale than Apple iPhone users.

3.2.1.2. Participants

The survey had 728 participants who self-selected to take part in response to advertisements. These adverts were placed within the University of Lincoln's participant pool, through posters around campus, on several social media sites, inside a local online and offline newspaper and through letters to local companies. The sample snowballed as this link was further shared online. As an incentive to take part, participants were told in the advertisements they would be entered into a prize draw to win a £50 Amazon voucher.

576 individuals finished the survey giving a completion rate of 79.12%. Of these, 186 (32.2%) were male, 387 (67.1%) were female and three (0.5%) described themselves as *"other"*. Age ranged from 15 – 74 with a mean age of 29.05 (SD = 13.107). Data on the smartphone people owned was also collected. 312 (54.1%) participants owned an Apple iPhone, 220 (38.1%) owned an Android phone, 22 (3.8%) owned a windows

phone, four (0.6%) owned an *"other"* smartphone, 15 (2.6%) owned mobile phones that were not smartphones, and three (0.5%) did not own a mobile phone at all. Overall this meant the sample contained 558 (97%) smartphone owners and 18 (3%) non-smartphone owners.

3.2.1.3. Ethics

The School of Psychology Research Ethics committee (SOPREC) based at the University of Lincoln approved the research before any data was collected. The study also adhered with British Psychological Society ethical guidelines for internet mediated research (Hewson et al., 2013). On the first page of the online survey, participants were presented with study information. No deception took place as the full aims of the study were described. Participants were also given the email address of the ethics committee which they could contact if they had any concerns. On this page, participants were presented with a random generated code which they could quote to the researchers if they wished to withdraw from the study. This allowed participant responses to be anonymous.

3.2.1.4. Procedure

The online survey provider Qualtrics was used to host the *"Smartphone Ownership and Personality Survey"* and was accessed via a public link. The first page of the survey described its contents and its purpose. Each respondent was additionally given a random anonymous ID number which they could quote to the researcher if they wished to withdraw their data. Participants were asked if they consented to take part and participant rights were outlined. Those who did not consent were directed straight to the debrief. Throughout the whole survey, a bar appeared along the bottom of each page to show respondents their progress.

Demographics such as age, employment status and gender were collected. Afterwards, participants were asked which smartphone they currently owned. Pictures were shown of Apple iPhones, Android phones and Windows phones to help participants identify their phone. The multiple-choice question also included the options *"I don't know"*, *"I don't own a smartphone, but I own a mobile phone,"* and *"I don't own a mobile phone of any type"*, to be inclusive to all phone and none phone owners. The length of time a participant had owned their current phone for in months (TOCP) was also collected. Respondents were then asked to select phones they had owned previously such as a *"Blackberry smartphone"* or *"A mobile phone which wasn't a smartphone"*.

After this, the AS, ASO, SES and the HEXACO-60 were administered. Once completed participants were asked if they wanted to view their HEXACO scores. Those who answered *"yes"* were presented with descriptions of each HEXACO factor alongside their score out of 50 for each trait. Finally, participants were presented with a debrief, were reminded of their anonymous participant number, were asked to leave an email address if they wanted to be placed in the prize draw and were given the researchers' contact details. Social media share buttons were also included along the bottom of the page which allowed participants to share the survey link on their own Facebook and Twitter sites. Overall, the survey consisted of 83 questions and took participants on average 39.5 minutes to complete.

3.2.2. Results

Raw data for this project is online and open access (see Ellis, 2016; Ellis, 2017).

3.2.2.1. Analysis Plan

The results are described across several sections. First, data manipulations are outlined, such as the data removal process and how scores for each scale were calculated prior to analysis. Secondly, assumptions for binary logistic regression were explored to assess the appropriateness of this analysis on the current data set. Thirdly, an overall binary logistic regression model containing all the variables was created using the 'Enter' method approach. Using the *B* coefficients of this original model to determine order, several binary logistic regression models were built hierarchically. This was conducted by adding variables one-by-one into binary logistic regression models to assess whether the particular variable significantly improved the models' fit to the data. A final, parsimonious model was created from variables which produced significant Chi-square improvements. This model was then tested on a separate sample of 221 participants, to see if it had predictive validity. To close the analysis, a conditional inference decision tree and a conditional inference random forest were built to model and visualise how variables can classify smartphone users into iPhone or Android user groups.

3.2.2.2. Data Removal

Several inferential statistics and models were used to assess psychometric differences between iPhone and Android users. These two groups made up 92.3% of the overall sample (*n*=532). However, three participants self-classified their gender as *"other"* so their data was removed from the analysis. This was to avoid having minimum expected frequencies under the value of five during binary logistic regression analysis. Overall, the subsequent analysis included 529 participants in which 310 (58.60%) were iPhone users and 219 (41.40%) were Android.

3.2.2.3 Coding

Each HEXACO trait was assessed using ten questions. The responses to the ten questions were averaged to create an overall score for that trait. As a result, each participant had six average trait scores which were used in the following analysis.

To generate scores for the rest of the variables average Attitudes Towards Similarity (AS) and average Attitudes Towards Mobile Phone as Status Object (ASO) scores were calculated for all participants alongside their raw Socioeconomic Status (SES), Age, and Time Owned Current Phone (TOCP) measures. See Table 3.2. for a list of summary statistics and internal reliability values for the scales used.

Table 3.2. List of measures/variables, summary statistics across the final sample (*n*=529). Reliability coefficients are calculated from the full sample of (*n*=576)

Measure	Number of items	Variable	*M*	*SD*	*α*
Age	1	-	28.74	12.94	-
Social economic status	1	-	5.99	1.52	-
HEXACO-60	10	Honesty-Humility	3.45	0.62	.76
	10	Emotionality	3.36	0.69	.83
	10	Extraversion	3.25	0.65	.80
	10	Agreeableness	3.14	0.61	.79
	10	Conscientiousness	3.56	0.60	.80
	10	Openness to experience	3.46	0.62	.76
Consumers need for uniqueness	4	Avoidance similarity	2.38	0.82	.89
Attitudes towards mobile phone as status object	6	-	2.25	0.59	.77
Time owned current phone (months)	1	-	12.11	9.98	-

SD = Standard Deviation, *M* = Mean, *α* = Cronbach Alpha Reliability Coefficient

3.2.2.4. Assumptions

Logistic regression model fitting does not require normally distributed data and can incorporate categorical predictor variables (e.g., gender). As such, this analysis was deemed most suited to the current data, as some, but not all predictor variables were normally distributed (see Fig. 3.1). To test for linearity of the logit, the natural log of age, honesty-humility, emotionality, extraversion, agreeableness, conscientiousness, openness to experience, AS, ASO, TOCP and SES scores were calculated. Then the interaction terms of each predictor and their logs were assessed. Nine out of ten interactions had significant values greater than 0.05, showing the assumption of linearity of the logit was met for all variables apart from age. Neither log or square root transformations on the variable age amended this violation, and reciprocal transformations inflated the *B* coefficients for age to an extreme value. Therefore, no transformations were applied. In addition, to test for multicollinearity between variables, Tolerance and VIF statistics were examined. None of the variables had a Tolerance value smaller than 0.1 or a VIF value greater than 10 indicating that all the predictor variables were independent from one another.

3.2.2.5. Binary Logistic Regression Analysis

The variable ‘smartphone’ was a binomial outcome variable, as there were two groups, iPhone, or Android ownership. Consequently, by fitting logistic regression models, it was possible to examine whether gender, age, TOCP, honesty-humility, emotionality, extraversion, agreeableness, conscientiousness, openness to experience, SES, AS and ASO were related to owning an iPhone or Android phone, and the direction of each relationship. First an overall model containing all the variables was created using the ‘Enter’ method approach. As there were minimal predictions concerning which variables would have greater coefficients, this was the least biased method when fitting the model. Android was used as the baseline category and therefore the model coefficients reflect the probability of owning an iPhone (see Table 3.3).

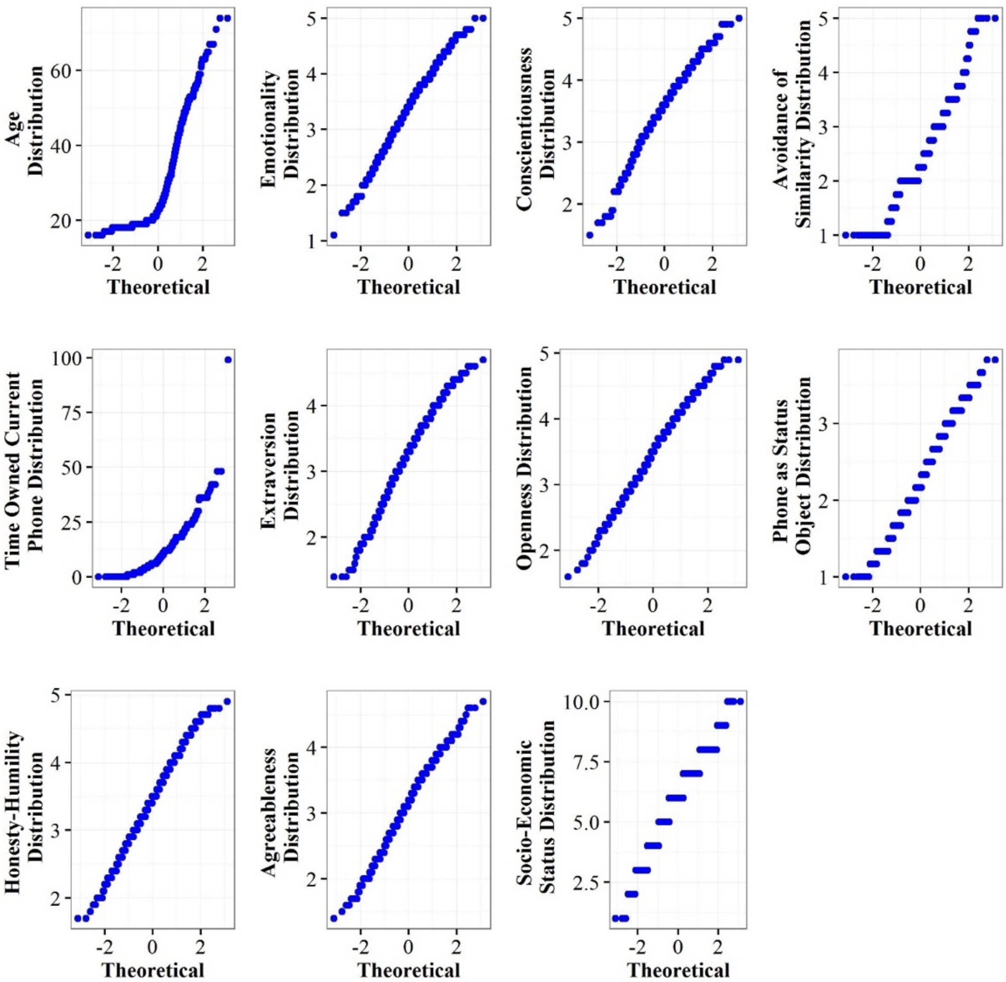

Figure 3.1. QQ plots for each variable. The distribution of the data is compared to a theoretical normal distribution for that variable, plotting each data point against its' normally distributed expected value. The closer the data is to the normal distribution, the greater the line will look in appearance to a straight and diagonal line.

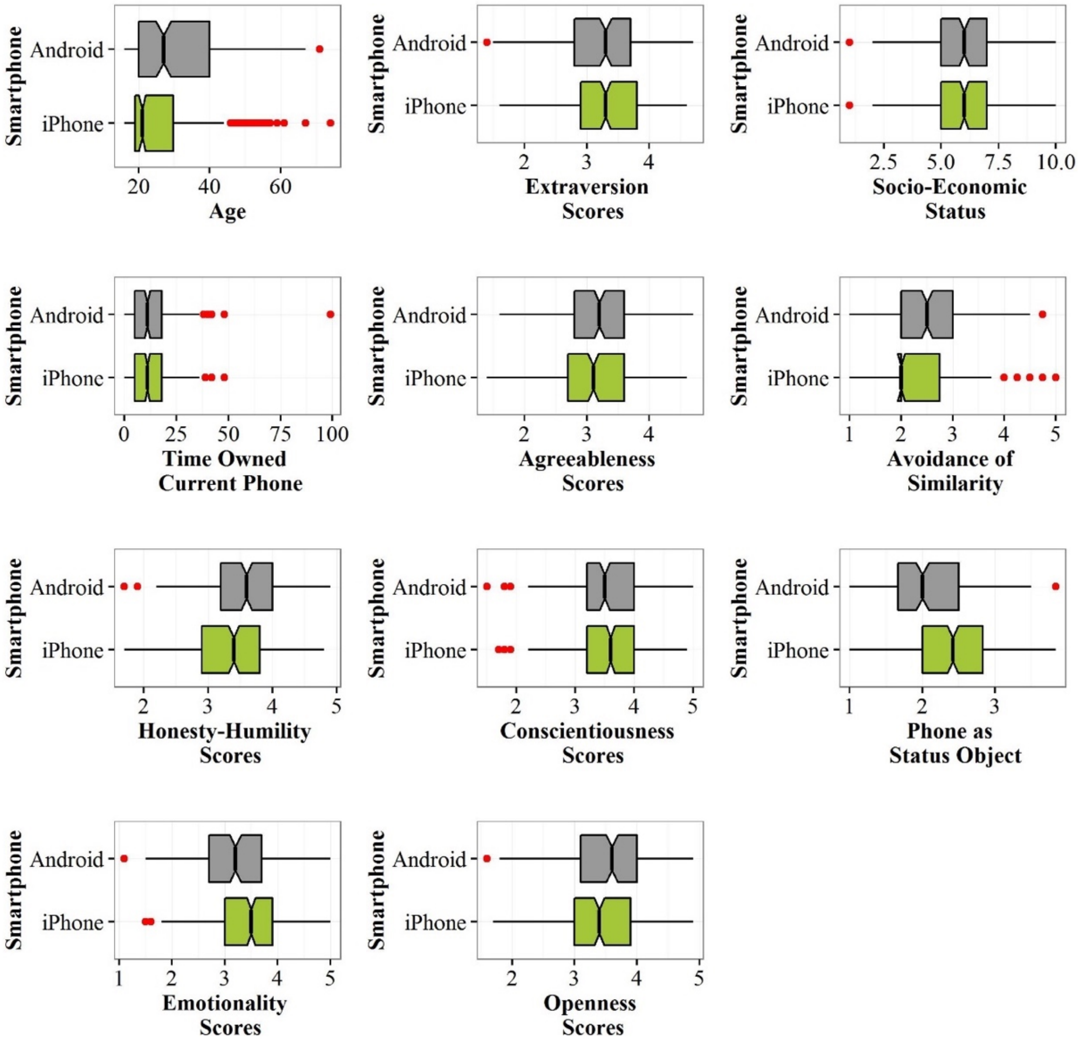

Figure 3.2. Box plots comparing the spread of data between iPhone and Android users for each variable. The notches display a 95% confidence interval around the median.

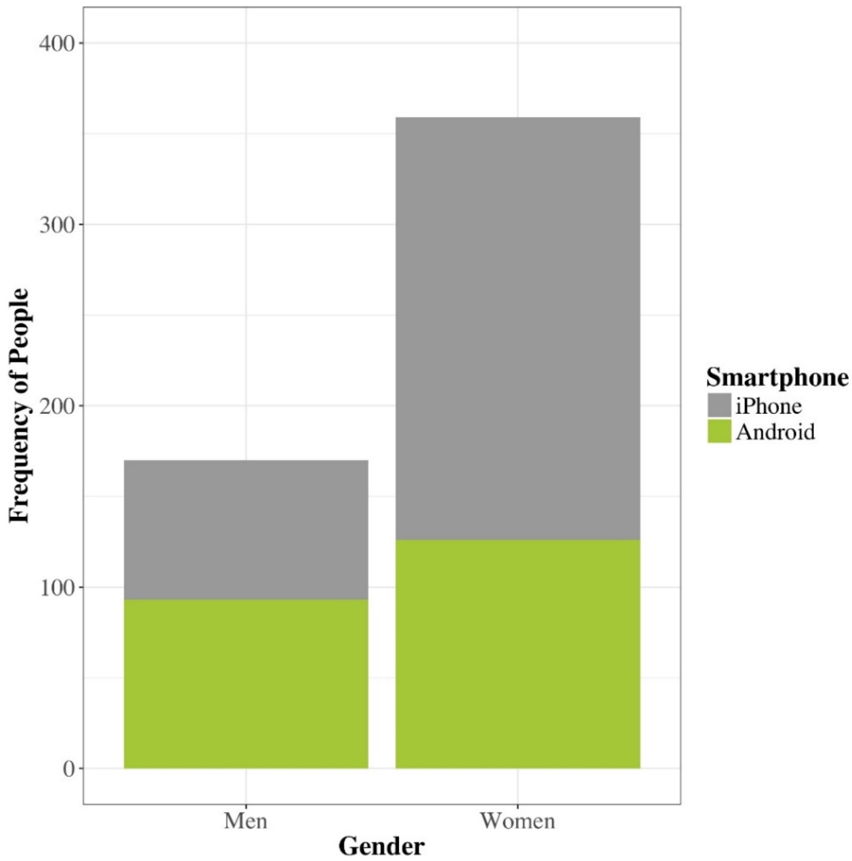

Figure 3.3. A Graph showing the frequency of Smartphone OS ownership between Men and Women.

Table 3.3. Coefficients from the 'Enter' method binary logistic model [$\chi^2(12) = 73.32$, p <.001] which includes all variables. $\boxed{R^2_{H\&L}} = .102$, $\boxed{R^2_N} = .174$ and $\boxed{R^2_{C\&S}} = .129$.

Variables	*B*	S.E	*z*	*p*	Exp(*B)*	95 % *C.I.* for *B* Lower	Upper
Intercept	-0.34	1.35	-0.26	.80	0.71	-3.01	2.30
Gender – (women)	0.64	0.23	2.8	<.01	1.89	0.19	1.08
Age	-0.01	0.01	-1.86	.06	0.99	-0.03	<0.001
Time owned current phone	<0.001	0.01	<0.01	>.99	1.00	-0.02	0.02
Honesty-Humility	-0.55	0.19	-2.85	<.01	0.58	-0.93	-0.17
Emotionality	0.16	0.16	1.01	.31	1.18	-0.15	0.48
Extraversion	0.32	0.16	1.97	<.05	1.37	<0.01	0.63
Agreeableness	0.04	0.17	0.24	.81	1.04	-0.29	0.37
Conscientiousness	0.28	0.17	1.64	.10	1.32	-0.05	0.62
Openness to Experience	-0.14	0.16	-0.88	.38	0.87	-0.47	0.18
Socio-Economic Status	-0.02	0.07	-0.26	.79	0.98	-0.15	0.11
Avoidance Similarity	-0.26	0.12	-2.22	<.05	0.77	-0.50	-0.03
Phone as Status Object	0.50	0.19	2.59	<.01	1.65	0.13	0.89

The results from the binary logistic regression analysis in Table 3.3. were then used to build 12 models hieratically. This was done by adding variables into a model one by one and then examining the Chi-square improvement (aka deviance) of the model as a result of adding that variable. The choice as to which variables should be incorporated first into models was based on the *B* coefficients from the previous binary logistic regression analysis as this indicated which variables would have the largest predictive value. The variable with the largest *B* coefficient was added first, and the variable with the next largest *B* coefficient was added second etc. The hierarchical model building was conducted because the Chi-square improvement statistic is a more accurate measure of assessing the individual contribution of each variable than the Wald statistic (z). This is because when the beta coefficient (B) is large, the standard error can become inflated resulting in the Wald statistic (z) being under-estimated. Again, Android was used as the baseline category and therefore, the model coefficients reflect the probability of owning an iPhone (see Table 3.4.).

	B. Smartphone											
Model	1	2	3	4	5	6	7	8	9	10	11	12
Gender (woman)	0.80***	.088***	0.84***	0.84***	0.81***	0.78***	0.64**	0.62**	0.63**	0.63**	0.64**	0.64**
Honesty-humility		-0.71***	-0.45**	-0.47**	-0.54**	-0.56**	-0.58**	-0.59***	-0.61**	-0.61**	-0.55**	-0.55**
Phone as Status Object			0.66***	0.65***	0.67***	0.62***	0.57**	0.53**	0.53**	0.53**	0.50**	0.50**
Extraversion				0.20	0.19	0.21	0.26	0.28	0.28	0.29	0.32*	0.32*
Conscientiousness					0.28	0.27	0.25	0.27	0.27	0.28	0.28	0.28
Avoidance Similarity						-0.29*	-0.27*	-0.27*	-0.27*	-0.27*	-0.26*	-0.26*
Emotionality							0.22	0.22	0.22	0.21	0.16	0.16
Openness to experience								-0.16	-0.17	-0.17	-0.14	-0.14
Agreeableness									0.06	0.05	0.04	0.04
Socio-Economic Status										-0.02	-0.02	-0.02
Age											-0.01	-0.01
Time owned current phone												<0.001
ROC Area	.59	.66	.69	.70	.70	.71	.71	.72	.72	.71	.72	.72
AIC	703.46	682.57	670.14	670.05	669.22	665.00	665.00	666.00	667.85	669.75	668.3	670.3
χ^2 improvement	18.16***	22.89***	14.44***	2.08	2.84	6.22*	2.00	1.00	0.14	0.11	3.46	<0.001

Table 3.4. Binary logistic regression models predicting smartphone ownership. The area under the ROC curve was calculated for each model, and the Akaike Information Criteria was also computed. By adding variables one by one, the increased χ^2 contribution for each variable was also calculated alongside whether this increase was significant. Note. $n = 530$. *B* = unstandardized regression coefficients. *Significant to $p < .05$ **Significant to $p < .01$. ***Significant to $p < .001$

The results of the hierarchal binary logistic regression analysis showed that gender [χ^2 (1) = 18.16, p <.001], honesty-humility [χ^2 (1) =22.89, p <.001], ASO [χ^2 (1) = 14.44, p <.001] and AS [χ^2 (1) = 6.22, p = .01] significantly improved the models fit to the data and contributed to the prediction of smartphone ownership. The Akaike Information Criteria (AIC) can identify overfitting, because it penalizes the model when increasing the number of coefficients by decreasing the reported model fit. After model seven, the AIC started to increase which indicated overfitting. As a result, only the four variables which had significant Chi-square improvements in model seven were used to build a final parsimonious model (see Table 3.5.). This final model could classify smartphone ownership with 68.8% accuracy, when comparing the classifications made by the model in comparison to the 529 actual classes (see Table 3.6.). This had a significantly better model fit [χ^2(4) = 61.43, p <.001] than a model with only the intercept.

In the final model, gender was the strongest predictor of smartphone ownership [B= 0.82, 95% CI = 0.43, 1.21]. When examining the odds ratio (Exp(B)) the odds of women owning an iPhone were 2.27 times higher than owning an Android (see Fig. 3.3.). Higher honesty-humility scores [B= -0.47, 95% CI = -0.81, -0.14], and higher AS scores [B= -0.28, 95% CI = -0.50, -0.05] decreased the probability of owning an iPhone. Alternatively, higher ASO scores increased the probability of owning an iPhone [B= 0.62, 95% CI = 0.27, 0.98]. As none of the negative relationships' confidence intervals were above zero, and none of the positive relationships' confidence intervals were below zero, it can be claimed that the directions of the B coefficients were robust in the population. None of the standardized or studentized residuals were over 1.96, showing that the error in the model was small enough to be a good fit to the data. No cases exerted undue influence over the parameters as Cooks Distance for every case was smaller than one. This suggests that the model will be stable across future samples.

Table 3.5. Coefficients from the final binary logistic model [$\chi^2(4) = 61.43$, p <.001] $\boxed{R^2_{H\&L}}$ = .086, $\boxed{R^2_N}$ = .148 and $\boxed{R^2_{C\&S}}$ = .11.

Variables	*B*	*S.E*	*z*	*p*	Exp(*B*)	95 % *C.I.* for *B* Lower	Upper
Intercept	0.72	0.91	0.80	-.43	2.05	-1.05	2.50
Gender – (women)	0.82	0.20	4.12	<.001	2.27	0.43	1.21
Honesty-Humility	-0.47	0.17	-2.76	<.01	0.63	-0.81	-0.14
Phone as Status Object	0.62	0.18	2.43	<.001	1.86	0.27	0.98
Avoidance Similarity	-0.28	0.11	-2.43	<.05	0.76	-0.50	-0.05

Table 3.6. Classification accuracy of the final model.

Smartphone Owned	Model's Predicted Classification Android	iPhone	Percentage (%) Correct
Android	115	104	52.53
iPhone	61	249	80.32
Overall %			68.8%

3.2.2.6. Empirical tests of the model

To further check the accuracy of the final model, an online test was created whereby a new sample of 221 participants were asked the same gender, honesty-humility, AS and ASO questions, as the initial study. A new approach for assessing reliability was created specifically for this project, and it involved using the *B* coefficients from the final model (see Table 3.5) to generate an algorithm which predicted ownership in 'real-time' whilst new participants were answering the same questions. Testing the predictive ability of *B* coefficients from the final model on a new data set ensured findings could be replicated outside the original study. This approach also goes beyond traditional methods when assessing classification accuracy, which typically involves splitting the original dataset into 1) data which trains the model (e.g., 75%), and b) data used to test the model's predictions (e.g., 25%) (Bali et al. 2016). The approach outlined here is arguably a more robust way to assess reliability. Moreover, it is also different to methods which run new data through pre-existing models to assess the model's accuracy. However, as the aim was to provide live feedback to participants, a new method was created to make this possible.

The online test provided participants with a prediction of what smartphone they would own dependent on their answers. This prediction was computed by running a scoring algorithm in the background of Qualtrics, so when the participant answered each question, a number was either subtracted or added to a cumulative score. The scoring algorithm was calculated as follows:

All participants started with a score of 0.

Gender: if *"Female"* was selected, the *B* coefficients of Gender from the final model was added to zero. If *"Male"* was selected, the *B* coefficients of Gender was subtracted from zero.

Avoidance of similarity: There were four questions in the avoidance of similarity scale. Therefore, the *B* coefficients of AS was divided by four. If a person selected *"Strongly Agree"* then *(* $\boxed{ß_{AS}}$ ÷ 4) was subtracted from the score, and if a person selected *"Strongly Disagree"*, ($\boxed{ß_{AS}}$ ÷ 4) was added to the score. If a person selected *"Neither Agree nor Disagree"*, zero was added to their score, so it remained the same.

If a person selected *"Agree"* ($\boxed{ß_{AS}} \div 8$) was subtracted from the score, and if a person selected *"Disagree"*, ($\boxed{ß_{AS}} \div 8$) was added to the score. This adjusted strength took into account the equal distance between the scale points, as *"Agree"* is halfway between *"Strongly Agree"* and *"Neither Agree nor Disagree"*.

Attitude towards mobile phone as status object: There were six questions in the ASO scale. If a person selected *"Completely Disagree"* ($\boxed{ß_{ASO}} \div 6$) was subtracted from the score. If a person selected *"Completely Agree"* ($\boxed{ß_{ASO}} \div 6$) was added to the score. *"Slightly Disagree"*, and *"Slightly Agree"* subtracted and added ($\boxed{ß_{ASO}} \div 12$) to the cumulative score respectively. This was consisted across all the questions, apart from those which were 'reverse' questions. In these cases, the outcome of adding or subtracting from the cumulative score was reversed.

Honesty-humility: There were 10 questions in the honesty-humility Scale. If a person selected *"Strongly Agree"* ($\boxed{ß_{HH}} \div 10$) was added to a score, and if a person selected *"Strongly Disagree"* ($\boxed{ß_{HH}} \div 10$) was subtracted from the score. If a person selected *"Neutral (Neither Agree nor Disagree)"*, zero was added to their score, so it remained the same. The response *"Agree"* added ($\boxed{ß_{HH}} \div 20$) to the score and *"Disagree"* subtracted ($\boxed{ß_{HH}} \div 20$) from the score. This was consisted across all the questions, apart from those which were 'reverse' questions. In these cases, the outcome of adding or subtracting from the cumulative score was reversed.

On completion, an overall positive score predicted that a person would own an iPhone, and a negative score predicted that a person would own an Android. Participants were provided with this prediction and were then asked whether this was correct. From the

200 participants who answered yes or no, the algorithm using the model's *B* coefficients performed at significantly above chance level, correctly identifying 69% of smartphone ownership. This matched the classification accuracy of the final model (see Table 3.6.) showing it had predictive validity. This increased to 71.4 percent correct when participants, who reported that they had previously owned the predicted device, were also included (n = 210).

3.2.2.6. Conditional inference tree and forest

Classification trees are logical structures that demonstrate how predictor variables (either continuous or categorical) are used to classify people into certain groups. The purpose of the current analysis was to train a decision tree which could classify Android or iPhone user groups, from their age, gender, honesty-humility, emotionality, extraversion, agreeableness, conscientiousness, openness to experience, AS, ASO, TOCP and SES scores. When visualized, trees portray a logical structure, denoting how a participant or case gets classified into a target variable group, based on a series of rules which have been extrapolated from the data (see Fig. 3.4). They are nonlinear, and instead use a process called recursive partitioning (Bali et al. 2016). This is where the data is split into smaller subgroups, based on the values within a chosen variable at each split. The aim is to partition the sample into purer and purer iPhone and Android groups. Conditional inference trees were chosen in comparison to CART and C5.0 trees as the splitting criteria is unbiased towards covariates with many possible splits (Hothorn et al. 2006). One advantage of this method is that the contribution of age can be modelled using decision trees and forests (an ensemble of trees) without violating any assumptions.

370 (70%) participants were used to train the tree and 159 (30%) participants were used to test the tree's predictions on 'unseen' data. Out of the 12 variables included in the model, only two, ASO and gender were chosen for splits. The resultant model had an overall classification accuracy of 67.29% on test data (see Table 3.7.) and was two decisions deep (see Fig. 3.4.). If a participant's ASO was greater than 2.5, they were classified by the model as an iPhone user. If a participant's ASO score was less than 2.5, then classification depended on their gender: Males were classified as Android users and females were classified as iPhone users.

Table 3.7. Classification accuracy of the decision tree model on test data.

Smartphone Owned	Model's Predicted Classification		Percentage (%) Correct
	Android	iPhone	
Android	25	41	37.87%
iPhone	11	82	88.17%
Overall %			67.29%

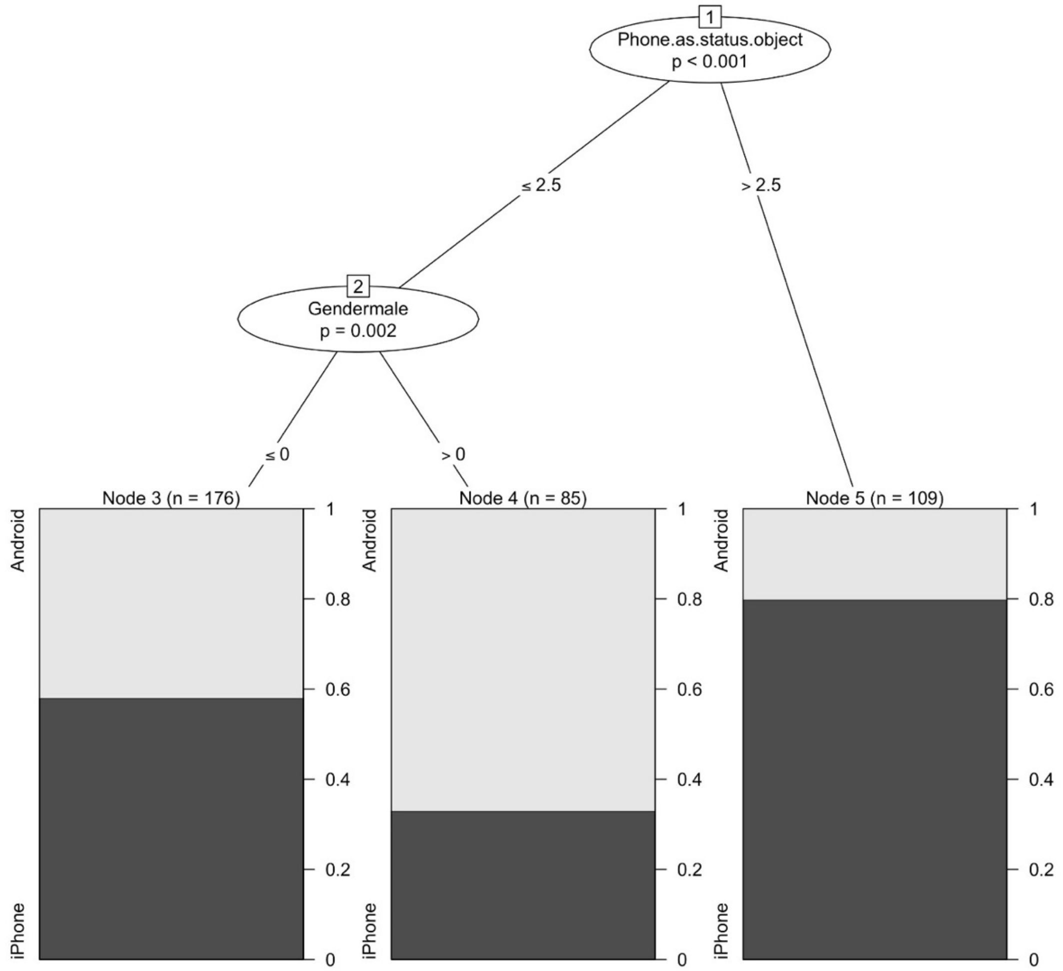

Figure 3.4. A Conditional Inference Tree predicting iPhone and Android ownership. Two variables, Phone as status object, and Gender were selected for splits. When splitting node two, due to dummy coding < 0 indicates female branch and > 0 indicates male branch. The proportion of iPhone and Android users are displayed in each terminal node with the predominant class being the model's prediction for that given path.

A conditional inference forest was also trained to predict smartphone ownership from the variables age, gender, honesty-humility, emotionality, extraversion, agreeableness, conscientiousness, openness to experience, AS, ASO, TOCP and SES scores. 370 participants were used to train the forest and 159 participants were used to test the forests predictions on ‘unseen’ data. The forest grown consisted of 500 trees with mtry = 7, meaning that out of the 12 variables, seven input variables were randomly selected as splitting candidates at each node. The forest had a classification accuracy of 65.4% (see Table 3.8.). Permuted importance was also calculated for each variable. This is the forests mean decrease in accuracy if a specific variables’ values are permuted. ASO had the highest importance score, followed by age (see Fig. 3.5.).

Table 3.8. Classification accuracy of the forest on test data.

Smartphone Owned	Model’s Predicted Classification		Percentage (%) Correct
	Android	iPhone	
Android	34	32	51.52%
iPhone	23	70	75.26%
Overall %			65.4%

Table 3.9. Cost metrics of the decision tree and conditional inference forest.

Metric	Decision Tree	Conditional Inference Forest
Accuracy	67.29	65.4
Precision	.67	.68
Recall	.88	.74
F1	.76	.71
Sensitivity	.88	.74
Specificity	.38	.50

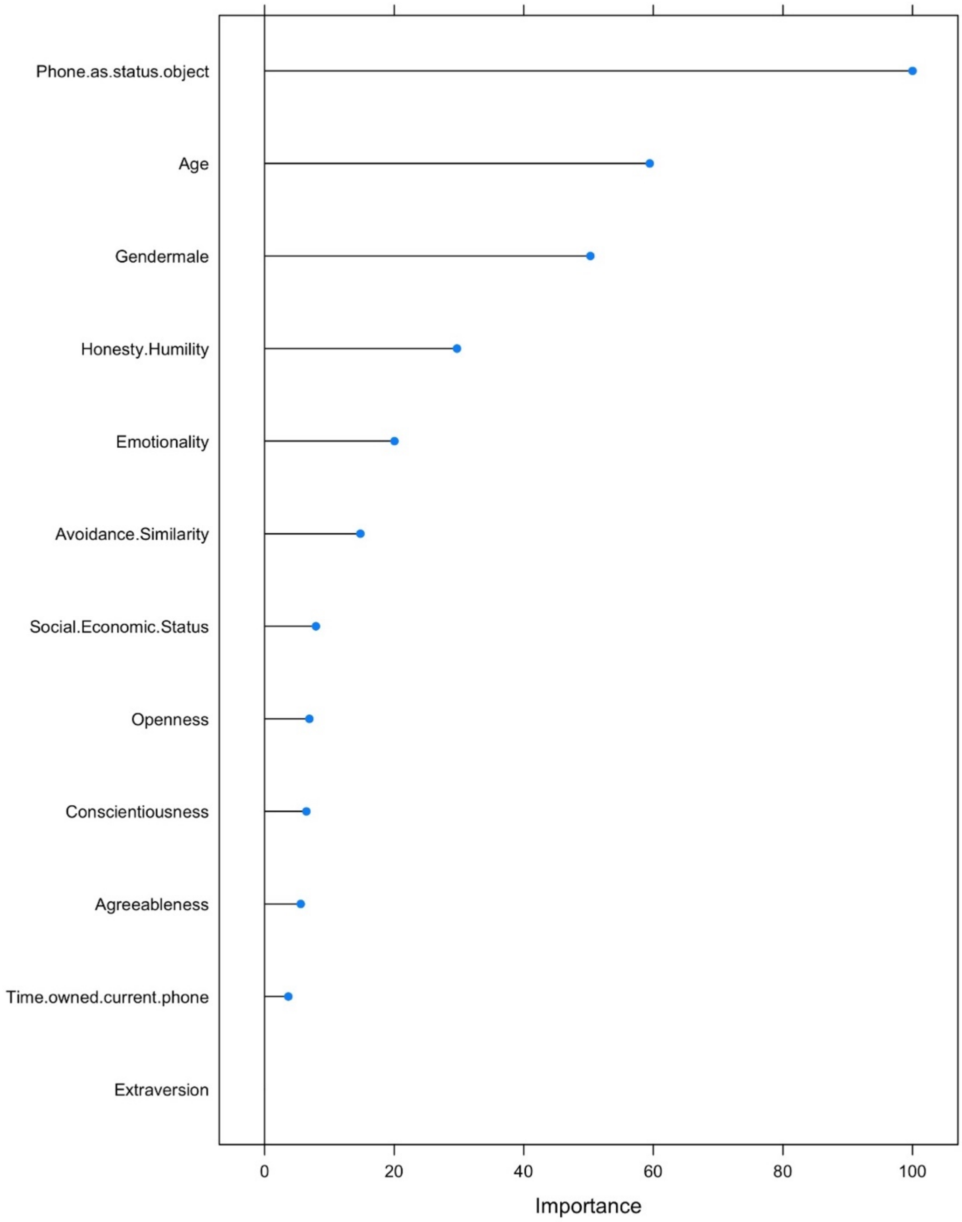

Figure 3.5. A graph showing the permutated importance of 12 variables in conditional inference forest, when predicting iPhone vs Android ownership.

3.2.3. Study One: Summary

Study one demonstrates for the first time that an individual's choice of smartphone operating system can provide useful information when it comes to predicting their traits and demographic characteristics. Smartphone ownership can consistently be predicted from user dispositions and demographics with between 65-70% accuracy across models. Notably gender was found to be the strongest predictor of smartphone ownership in binary logistic regression modelling, whereby the odds of women owning an iPhone were 2.27 times higher than owning an Android. When examining HEXACO personality differences (Ashton & Lee, 2009) results showed that higher amounts of honesty-humility were more indicative of Android ownership during binary logistic regression modelling. However, no other core personality factor consistently predicted ownership. Therefore, hypothesis one was rejected, as extraversion did not significantly improve model fit when conducting hierarchical binary logistic regression analysis, and equally was not shown as an important predictor variable in decision tree and random forest analysis. Likewise, hypothesis two was also rejected as socio-economic status did not add predictive value across models. However, this study did find support for hypothesis three, predicting that user traits would be congruent with the brand personality of the operating system they choose. Higher amounts of ASO increased the likelihood of owning and iPhone, and higher AS scores increased the likelihood of owning an Android across all models. Notably ASO was the most important predictor in both decision tree and random forest models, whereby this variable in conjunction with gender alone could predict ownership with 67% accuracy (see Table 3.8).

Interestingly, age did not predict smartphone ownership across binary logistic regression models but instead was a useful predictor variable across hundreds of tree models in the random forest modelling. This may be due to the fact that age violated linearity of logit assumptions during binary logistic regression analysis, and therefore could not be effectively modelled using this method. It has been shown that, random forests have improved accuracy in comparison to traditional regression models when used on data that violates assumptions (Merkle & Shaffer, 2011). Therefore, age should be considered an important predictor of smartphone ownership and should not be disregarded.

As differences were found to arise between iPhone and Android users, it is of interest to next examine whether stereotypical ideas had formed about the personality and behaviours of these two user groups. If the personalities of users are indicative of the advertising campaigns produced by each brand, then there may be two possible sources of social representation formation; an individual's personal experience of each type of smartphone user, and the media's conveyed personality of the brand.

3.3. Study Two: Examining Stereotypes Associated with Smartphone OS

In study one, participants were asked to identify adjectives and differences they associated with iPhone and Android users. Based on social representations theory, it was predicted that people would describe iPhone users and Android users in unique ways (Augoustinos et al., 2009; Moscovici, 1984). Notably it was predicted that iPhone users would have the stereotype of being more sociable (hypothesis four) than Android users (Götz, Stieger & Reips, 2017; Smith, 2013; Hixon, 2014; Bjelland et al., 2012).

3.3.1. Method

3.3.1.1. Materials

Participants were asked to circle adjectives that they associated with iPhone and Android smartphone users. Adjectives were taken from Lee & Ashton (2008), whereby 160 adjectives were listed, and each adjective was either synonymous or antonymous with one of the six personality factors specified in the HEXACO-60 (Ashton & Lee, 2009). These adjectives were chosen so that stereotyped HEXACO personality traits could be directly mapped to the 'actual' personality traits in study one. This list of adjectives was also chosen as it contained familiar English words that participants could easily comprehend. The list was brief and could be read quickly, enabling a larger sample size to be obtained. All the words are listed in appendix one.

The list of 160 words was randomised across participants and questions. Randomisation was achieved through the use of a custom built visual basic programme, which imports text files and outputs a randomised list of words. Participants were required to read this list twice, once for iPhone users and once for Android users, but on each occasion, the words would be in a different order. This encouraged parity in the participants' answering techniques between the questions, as participants had to thoroughly read both lists and would not be able to identify the location of a particular word from memory.

3.3.1.2. Participants

An opportunity sample of 243 people on the University campus took part in the study. Participants were told that they would be entered into a prize draw to win a £50 Amazon voucher as an incentive to take part. Ages ranged from 18-67 (*M*=24.67). Of those who provided their gender details (*n*=235), 144 participants were women (61.2%) and 91 were men (38.7%). Participants had a variety of employment statuses. Data on phone ownership was also collected (*n*=236). Android Phone users made up 36.8% of the sample (*n*=87), Apple iPhone users made up 57.62% of the sample (*n*=136), Windows Phone users made up 3.3% of the sample (*n*=8) and 2.1% were classed as other (*n*=5). The other category included people who either did not own a phone or smartphone or owned a combination of the above.

3.3.1.3. Ethics

The School of Psychology Research Ethics committee (SOPREC) based at the University of Lincoln approved the research before any data was collected and complied with BPS ethical procedures (British Psychological Society; 2018). Participants were given a consent form, which stated several participant rights, such as the ability to withdraw, ask questions, anonymity and outlined how the data would be stored before taking part. Participants were told the full aims of the study prior to consenting and were adequately debriefed.

3.3.1.4. Procedure

Data was collected over two days at various sites on the University campus. The researchers asked an opportunity sample of those present if they were willing to take part in *"a study researching whether people think there are personality differences between Apple iPhone and Android Phone users"*. Those who wanted to participate were provided with a four-page booklet. The first page included a consent form outlining of the aim of the research, the rights of the participant, and the researcher's details. Participants were encouraged to fully read the booklet before providing consent. The second page contained the question *"Do you think there are personality differences between iPhone and Android users?"*. Participants were required to circle *"yes"* or *"no"* to this question, and if yes, were asked a second open ended question *"What personality differences are there?"*. Additionally, on the second page of the booklet, demographic information was collected including age, gender, current phone, employment status and email address. On pages three and four, participants were asked to circle adjectives which they associated with iPhone and Android Phone users. The iPhone and Android list of adjectives were presented on separate pages, and this was randomised between participants. Therefore, 50% of participants completed the question relating to iPhone users first before moving on to Android users. The remaining 50% completed the questions in the reverse order. After the booklet was completed, participants were thanked for their time and debriefed.

3.3.2. Results

3.3.2.1. Analysis Plan

Stereotypes towards iPhone and Android users were analysed in several steps. First, the frequency of people who answered *'yes'* or *'no'* to the question *"Do you think there are personality differences between Apple iPhone and Android Phone users?"* was explored. Following, content and sentiment analysis was conducted on written responses which described personality differences between iPhone and Android users. Finally, the frequency of circled adjectives that were synonymous and antonymous to each of the six HEXACO traits were compared when describing iPhone and Android users.

243 people took part in the survey, however three withdrew their data. This left 240 responses for analysis. When asked the question *"Do you think there are personality differences between Apple iPhone and Android Phone users?"* 103 (42%) responded *'yes'*, 133 (55%) responded *'no'*, two (0.8%) circled both *'yes and no'* and two (0.8%) did not answer the question. Interestingly, 111 out of the 133 people who answered *'no'* to this question, chose to circle adjectives which they associated with iPhone and Android users, and did not leave this blank. This implies that these participants were aware of the social representations and stereotypes attached to the smartphone users, even if they did not personally agree that there were differences. As the current research was interested in measuring the stereotypes associated with iPhone and Android users, this data was kept in the analysis.

3.3.2.2. Content and Sentiment Analysis

Those who answered *"yes"* to the question *"Do you think there are personality differences between Apple iPhone and Android Phone users?"* were asked *"What personality differences are there?"* 109 responses were recorded, and 98 were from those who answered *'Yes'* to the previous question. Answers were between 1 and 17 words long. As such, content and sentiment analysis were conducted on this text data.

To prepare the data for analysis, numbers, punctuation and stop words were removed. All text was made lower case and common words not relating to individual differences were removed. This included the words: 'users', 'phones', 'phone', 'mobile', 'tend', 'difference', 'don', 'differences', 'user', 'iPhone', 'apple', 'android', 'androids', 'iPhones', 'samsung', 'iOS', 'galaxy', 'people'. Once these were removed, a list of terms was created and contained 362 unique words (see Fig. 3.6.) Next, the ten most frequently mentioned terms were examined (see Fig. 3.7.). The words 'money', 'technology', 'brand', 'products', 'image', 'product', 'interested', 'social', 'arrogant' and 'care' were most frequently mentioned. Sentiment analysis was conducted using the 'bing' lexicon as the dictionary of choice from the 'tidytext' R package (De Queiroz, et al. 2018). This dictionary categorised words in a binary fashion, whereby each word was coded as either 'positive' or 'negative'. Overall, responses had greater positive sentiments than negative; 39 words were classified as negative, whereby 63 words were classified as positive.

Figure 3.6. Word cloud of the 362 words mentioned when asking participants to describe personality differences between iPhone and Android users.

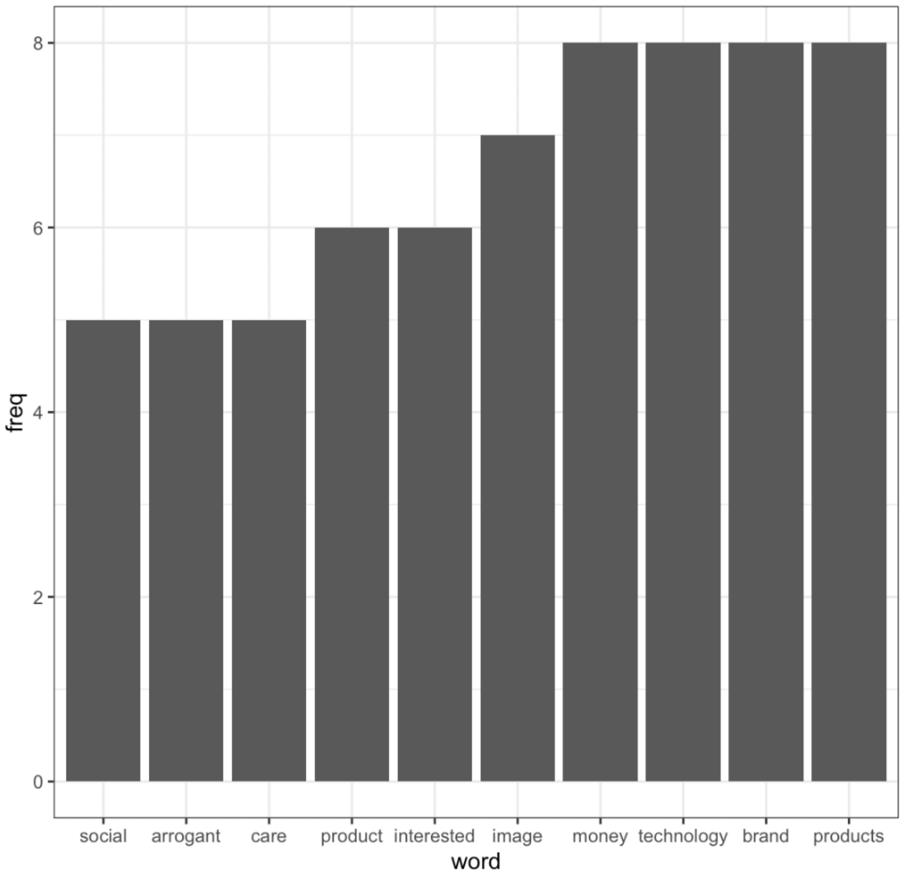

Figure 3.7. When asked to describe personality differences between iPhone and Android users, this graph shows the ten most frequently mentioned terms from 109 responses.

3.3.2.3. Adjective Analysis

To create scores for the analysis, the frequency of circled adjectives that were synonymous and antonymous to each of the six HEXACO traits were calculated for Apple iPhone and Android Phone users separately (see Appendix A; list derived from Lee & Ashton, 2008). This created 12 scores per smartphone user group (six antonymous and six synonymous with HEXACO), which was then used in the analysis. To test for normality of these new variables, 24 Shapiro-Wilk tests were conducted. The distribution of all 24 variables were significantly different from a normal distribution (all p's <.05), being positively skewed. As such, a non-parametric test, Wilcoxon rank-sum was chosen to make the 12 comparisons. Due to the positive skew, measures of central tendency were close to zero, and in some cases the median values did not highlight the direction of significant results. Consequently, means are also reported.

Table 3.10. Descriptive statistics when analyzing the frequency of circled adjectives used to describe iPhone and Android users in each personality category.

	iPhone Users				Android Users			
Synonymous	Median	Range	Mean	*SD*	Median	Range	Mean	*SD*
Extraversion	2	14	2.73	2.78	1	14	1.65	2.26
Conscientiousness	1	9	1.15	1.56	1	14	1.41	2.09
Honesty-Humility	0	11	0.86	1.64	0	14	1.79	2.78
Agreeableness	0	7	0.71	1.29	1	14	1.56	2.33
Emotionality	0	6	0.69	1.14	0	14	0.68	1.50
Openness to Experience	0	8	0.77	1.3	1	14	1.24	1.96
Antonymous								
Extraversion	0	6	0.30	0.78	0	14	0.84	1.69.
Conscientiousness	0	11	0.53	1.35	0	14	0.65	1.50
Honesty-Humility	1	12	1.66	2.28	0	14	0.49	1.34
Agreeableness	0	10	1.23	2.05	0	14	0.68	1.54
Emotionality	0	8	0.62	1.23	0	14	0.48	1.21
Openness to Experience	0	4	0.50	0.83	0	6	0.50	0.86

Results of the Wilcoxon rank-sum tests showed that adjectives synonymous with extraversion were circled in significantly higher frequencies when describing iPhone users (M = 2.73) than Android users (M = 1.65) [W = 35668, p = < .001, r = -.30]. This pattern was mirrored when examining adjectives antonymous with extraversion as the frequency of circled adjectives was significantly more when describing Android users (M = 0.84) than iPhone users (M = 0.30) [W = 23436, p <.001, r = -.29]. In addition, Android users (M = 1.79) were described with significantly more adjectives synonymous with honesty-humility than iPhone users (M = 0.86) [W = 24070, p = <.001, r = -.22] and Android users (M = 0.49) were described with significantly less adjectives antonymous with honesty-humility than iPhone users (M = 1.66) [W = 38794, p = <.001, r = -.49].

Differences were also found when examining the frequency of adjectives synonymous and antonymous with agreeableness. Android users (*M* = 1.56) had significantly higher amounts of circled adjectives synonymous with agreeableness than iPhone users (*M* = 0.71) [*W* = 22630, *p* <.001, *r* = -29]. Unsurprisingly, significantly less adjectives antonymous with agreeableness were circled when describing Android users (*M* = 0.68) than iPhone users (*M* = 1.23) [*W* = 33968, *p* <.001, *r* = -.25]. The personality trait openness-to-experience had contradictory results. Whilst significant differences were found when examining the frequency of circled adjectives synonymous with openness-to-experience for iPhone (*M* = 0.77) and Android users (*M* = 1.24) [*W* = 24888, *p* = .001, *r* = -.18], no differences were found when measuring the frequency of antonymous adjectives [*W* = 28838, *p* = .1, *r* = -.002]. Finally, no differences arose when examining adjectives synonymous with conscientiousness [*W* = 28052, *p* = .60, *r* = -.03] and emotionality [*W* = 30884, *p* = .11, *r* = -.10] or adjectives antonymous with conscientiousness [*W* = 27636, *p* = .33, *r* = -.06] and emotionality [*W* = 30118, *p* = 0.28, *r* = -.07].

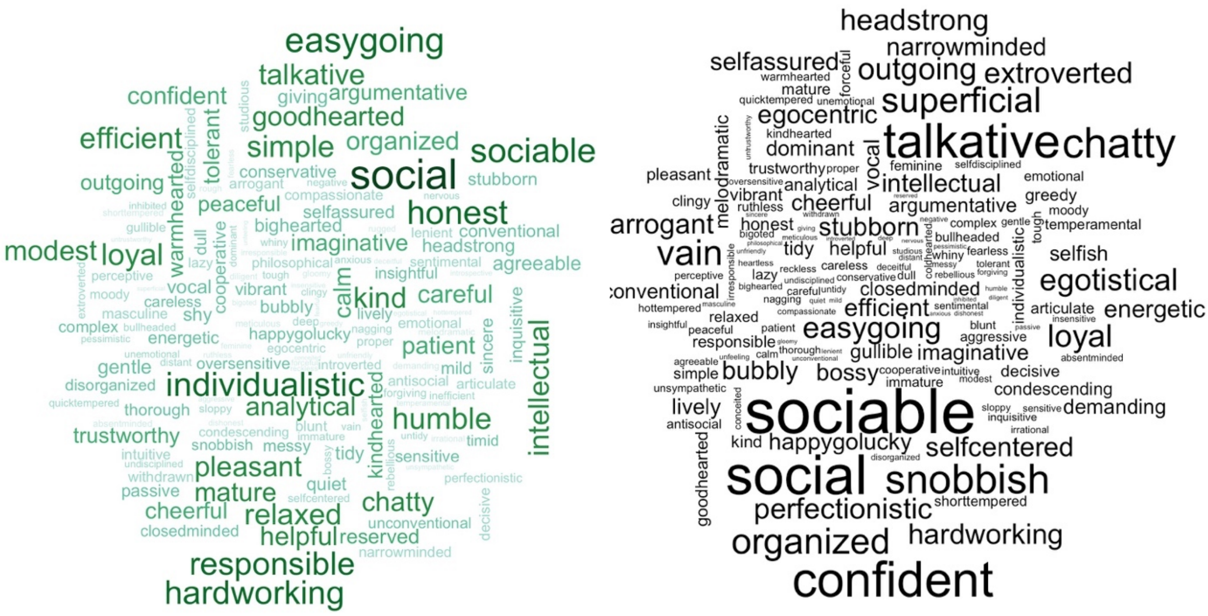

Figure 3.8. Word clouds representing the most frequently circled words when asked to circle adjectives associated with Android (left) and iPhone users (right).

3.3.3. Study Two: Summary

The results of study two suggest that there are unique social representations about users of different smartphone brands in line with Social Representations Theory (Augoustinos et al., 2009; Moscovici, 1984). Notably these differences related to levels of extraversion, honesty-humility, and agreeableness. In line with hypothesis four, iPhone users were perceived to have more extraverted attributes than Android users. Additional findings included that iPhone users we less associated with agreeable and honesty-humility traits than Android users. However, whether participants believed these social representations to be 'true' is under debate as 133 out of 240 participants thought there were no actual differences between the users. This suggests that for half the participants, any stereotypes or adjectives they circled were purely a social representation, rather than a reflection of their personal experience.

In contrast, 103 participants believed there to be genuine differences in the personality traits of iPhone and Android users. Content analysis also showed that money was frequently mentioned as a difference between iPhone and Android users. This is in line with previous research suggesting that owners of different smartphone brands vary in wealth (Götz, Stieger & Reips, 2017). Other frequently mentioned terms included the 'brand' and 'product' as important factors when contemplating differences between owners of different devices. This may be referencing how users evaluate their phone as a status object, which was an important predictor in study one when differentiating between iPhone from Android users. Overall, differences between iPhone and Android users were discussed more frequently with a positive sentiment than with a negative sentiment.

3.4. Discussion

3.4.1. Convergence with prior work

The pivotal question in Chapter 3 concerned whether the simplest technological personalisation, in the form of choosing a smartphone operating system, would reveal characteristics about a user's dispositions and demographics. This was explored by examining the personality traits of iPhone and Android users. Study one demonstrated that particular behavioural and demographics qualities can be attributed in greater amounts to one smartphone brand than another showing that smartphone operating system alone is enough personalisation to start inferring information about the end user. Whilst effect sizes in study one varies from small to medium, this is likely a reflection that choice of smartphone is the most basic level of technology personalisation. Belk's extension of self-theory posits the more power and control a person has over the technology, the more it will extend them (McClelland, 1951; Belk, 1998). Therefore, as an owner continues to personalise their device through using it in distinctive ways it is predicted that larger unification would show.

The demographics, age and gender were found to predict smartphone ownership. Notably, iPhone users were more likely to be female than Android users. Other research suggests that when shopping for a new device, men gravitate towards the technical aspects of mobile phones such as operating system, battery life, screen size and processor speed in comparison to women who pay greater attention to price, service contract terms and camera capabilities (Nielsen, 2014). In addition, gender has previously been shown to predict the use of social, e-commerce, productivity, sport, and other mobile applications (Stachl et al. 2017; Kim, Briley & Ocepek, 2015, Quin et al., 2018). As gender showed the largest effect size in study one whereby the odds of women owning an iPhone were 2.27 times higher than owning an Android, it is possible that both smartphone brands have particular affordances which attract those of each gender to its features.

Age was also an important predictor of smartphone ownership which is consistent with other research suggesting that technology use is age dependant (Vorrink et al. 2017; Gell et al. 2015; Christensen et al. 2016). Windows users are on average older than Mac OS users (Götz, Stieger & Reips, 2017). In a cross-sectional sample of older adults, a survey showed that ICT use decreases with age (Vorrink et al. 2017). In a similar survey of 7609 individuals, higher prevalence of technology use was associated with younger age and being male (Gell et al. 2015). A younger demographic is also related to increased smartphone use when measuring screen time (Christensen et al. 2016). Whilst these findings highlight a potential digital divide in the way people use technology, the findings from study one show this may also be prevalent in the ownership of particular devices. However, as both iPhone and Android operating systems have a wide library of available applications and share their ability to access the internet and download social networking applications, it is likely that this digital divide is the result of more specific features such as money, technology, brand, social and image qualities of iPhone and Android phones, mentioned in the content analysis of study 2.2.

In study one, when examining HEXACO personality differences (Ashton & Lee, 2009) results showed that higher amounts of honesty-humility were more indicative of Android ownership during binary logistic regression modelling. People with higher amounts of honesty-humility *"avoid manipulating others for personal gain, feel little temptation to break rules, are uninterested in lavish wealth and & luxuries, and feel no special entitlement to elevated social status"* (Lee & Ashton, 2016). However, no other core personality factor consistently predicted ownership, and showed less importance than ASO, age and gender in random forest modelling. This has implications for researchers who create studies and experiments using one operating system alone (Götz, Stieger & Reips, 2017). If researchers control for age and gender, then findings for the most part can be generalized to others with differing personalities. Researchers should however be cautious with studies that examine behaviors which may be influenced by differing honesty-humility dispositions. Overall, this result shows the usefulness of using the HEXACO personality model (Ashton & Lee, 2009) over 'Big 5' approaches (Maltby, Day, & Macaskill, 2010) as this variable would have not been explored using an alternative model of personality.

Study one demonstrates that brand personalities, portrayed in current advertising campaigns were found to be congruent with the dispositions of those who use their respective operating systems. Smartphones are important social devices, allowing people to communicate across instant message, phone calls and social media. However, smartphones have an additional social role beyond this, as iPhone users place importance on their phone being a status object, elevating their social standing. In this scenario, it can be speculated that using a particular smartphone brand, helps the user to become closer to their ideal self (Koo, Cho & Kim, 2014; Hosany & Martin, 2012). In contrast, the finding that Android users ‘avoid similarity’ by avoiding popular products may be an example of owning a product that extends their current self and maintains their existing identity (Belk, 1998; Belk, 2013). Whilst this study cannot ultimately decide which mechanism of amalgamation is instigating the similarities between owners and product, it is possible that a combination of both means results in these similarities. However, brands should have awareness of their distinct personality (Aaker, 1997), as this is related to the type of person who owns their products.

In study two, iPhone users were perceived to have more extraverted attributes and were less associated with agreeable and honesty-humility traits than Android users. It is possible that social representations may have formed about iPhone and Android users through two types social information; Anchoring may have occurred through receiving information from media and through personal exposure to each user group (Augoustinos et al., 2009; Moscovici, 1984). Stereotypes have previously been linked to producing hate speech in online social media platforms (Chetty & Alathur, 2018), and for the first time, this project shows that stereotypes can form around the technology a person chooses to own. However, by comparing the results of study two to study one, some of these stereotypes did not match the personality traits each brands’ users. Notably, extraversion and agreeableness did not differ between the smartphone user groups, despite preconceptions in study two. Thus, like other dichotomous groups such as single vs. coupled, only child vs siblings, and those who wear glasses vs. those who don’t, stereotypes can form about owners of particular technology brands, which may not be representative of users in each group. (Borkenau, 1991; Greitemeyer, 2009; Hellström & Tekle, 1994; Mõttus et al., 2008).

Consequently, it appears that computational algorithms such as decision trees and random forests could be a better candidate when predicting a user's personality traits over traditional observer ratings (Hinds & Joinson, 2019; YouYou, Kosinski & Stillwell, 2015).

3.4.2. Limitations

Beyond demographic predictors (e.g., age and gender), the use of psychometric over behavioural measures could be viewed as a limitation. However, personality assessments have been shown to portray the core dispositions of a person which subsequently have been used to predict behaviour in many situations (Fleeson & Jayawickreme, 2015). As a result, it can be argued that the models are informative of how users will behave in real life scenarios. A second limitation concerns how ownership was determined. It is possible that some participants in the sample did not choose the smartphone that they currently own. Some participants could have received the smartphone as a gift, and younger participants may have had a parent or guardian purchase the phone on their behalf. Of course, these participants may still 'embody' the semantics attached with each smartphone brand, but future research would need to consider cause and effect.

This study also explored whether there were economic factors influencing smartphone ownership. However, in opposition to previous research (Smith, 2013; Hixon, 2014) SES did not predict smartphone ownership in study one. It remains difficult, however, to disregard the idea that financial differences do not exist between smartphone users. For example, the way individuals choose to spend disposable income, and how they prioritize the things they buy may still be indicative of smartphone ownership. Money was frequently mentioned when contemplating differences between iPhone and Android users in study two suggesting that the variable 'perceived social economic status' may have not captured nuanced differences in spending and wealth. The absence of differences in social economic status may have also occurred due to a younger average age (M = 29.05) in study one, in comparison to what would occur in the general population.

3.4.3. Conclusions

In conclusion, smartphone ownership can consistently be predicted from user dispositions and demographics with between 65-70% accuracy across models. This suggests that smartphones and owners experience a type of amalgamation, that allows their identity to be predicted from the technology they own by either extending their self-identity through their smartphone choice or embodying the semantics attached to each brand (Adam & Galinsky, 2012; Belk, 2013). This has implications when recruiting solely either iPhone or Android user's in psychological research. Notably, where possible, it is advocated that studies recruit from both platforms to allow for results to generalise across both types of users. However, if this is not possible, researchers could control for age and gender, (and if relevant, honesty-humility and phone as status object) during recruitment and analysis. Findings from chapter three also have implications for user privacy if age and gender can be reliably predicted from device ownership (Qin et al. 2018). However, targeted advertising and companies which execute personalised search results may benefit from learning this information, without requiring the user to disclose this themselves (Quin et al. 2018).

To reach a balance, it may be possible to impose limits on the amount of digital data companies can trace from a user if operating system alone can provide enough information for this purpose. Nevertheless, this is a topic of ongoing debate. For the consumer it may be possible to recommend certain devices that are 'better suited' to the user, based on their demographics, in a similar approach to personalised application suggestions (Yan & Chen, 2011). But overall, the results of this chapter show that key information about a person can be derived from the simplest of digital traces - an individual's smartphone operating system of choice. The next chapter continues this work by exploring methods of capturing simple usage traces across both iPhone and Android devices.

Chapter 4

Exploring objective measures of smartphone use.

The following chapter forms part of the publications:

Andrews, S., Ellis, D. A., Shaw, H., & Piwek, L. (2015). Beyond Self-Report: Tools to Compare Estimated and Real-World Smartphone Use. *Plos One*, *10*, e0139004. https://doi.org/10.1371/journal.pone.0139004

Wilcockson, T. D. W., Ellis, D. A., & Shaw, H. (2018). Determining Typical Smartphone Usage: What Data Do We Need? *Cyberpsychology, Behavior, and Social Networking*, *21*, 395–398. https://doi.org/10.1089/cyber.2017.0652

Ellis, D. A., Davidson, B. I., Shaw, H., & Geyer, K. (2019). Do smartphone usage scales predict behavior? *International Journal of Human Computer Studies*, *130*, 86–92. https://doi.org/10.1016/j.ijhcs.2019.05.004

4.1. Introduction

In chapter three, it was found that a very basic digital trace, the smartphone operating system (OS) a person uses, can provide information about individual differences. Moving beyond OS ownership, it is conceivable that the time a person spends on their device might also be informative of their characteristics. For example, the frequency of 'screen on' events at certain times of the day can be used to determine chronotypes; whether someone is a 'morning' or 'evening' person (Aledavood, Lehmann, & Saramäki, 2018). Therefore, simple traces such as timestamped on/off data could provide information on a person's daily routine and sleep patterns (Aledavood, Lehmann, & Saramäki, 2015). Further, the times of day a person uses their smartphone has been shown to vary between people but is relatively consistent within the same person (Aledavood, López, et al., 2015; Harari et al., 2019). It is therefore possible that temporal patterns of smartphone use can also provide markers for specific user characteristics. This chapter therefore investigates how to methodologically capture time spent on smartphones, by comparing and contrasting different measurement tools.

There are numerous existing studies which examine the length of time people spend on their phones, for example, across a day or week. These often examine the relationship between longer use and aspects of personality, cognition, and health (Christensen et al., 2016; Haug et al., 2015; Hussain, Griffiths, & Sheffield, 2017; Katevas, Arapakis, & Pielot, 2018; Marty-Dugas, Ralph, Oakman, & Smilek, 2018; Przybylski & Weinstein, 2017; Rideout, 2016; Rozgonjuk, Levine, Hall, & Elhai, 2018; Wilcockson, Osborne, & Ellis, 2019). Within these studies, one review showed that it was popular to measure smartphone use by asking participants to estimate their usage frequency (40% of papers), durations of use (27% of papers) or through other forms of self-report measures (9% of papers) (Boase & Ling, 2013). There has also been a rise in the creation of psychometric scales which aim to measure elements of smartphone use (Ellis, 2019). Despite this, little effort has actually been placed on assessing the validity of self-report measures and there is currently no consensus on what the best way is to measure usage behaviours.

This lack of consistency in measures makes it difficult to compare findings across studies, especially when a change in measurement can produce different conclusions. For example, a meta-analysis of 37 studies found that measuring smartphone use, through psychometrics scales such as ‘The Smartphone Addiction Scale’ (Kwon et al., 2013), showed a stronger association with stress and anxiety than frequency estimates of use (Vahedi & Saiphoo, 2018). This poses ethical problems if findings are used to advocate treatments, interventions or policy changes from results which cannot be replicated across studies.

There are also problems in the way some measurement tools are conceptualised. Notably, using a psychometric scale to ‘measure problematic smartphone use’ is prevalent in the literature, and aim to capture “excessive use” or “overuse” (Elhai & Contractor, 2018; Elhai, et al, 2020; Kim, 2017; Yang et al., 2019). This has foundations in the behavioural addictions framework whereby tolerance is a key component (the need to increase use over time to get the same ‘fix’) (Billieux, et al, 2015; Elhai et al., 2017; Kim, 2017). Therefore, it is part of the conceptualisation of problematic smartphone use to measure ‘excessive’ time spent on the device, through asking people respond on a rating scale to questions such as *“Using my smartphone longer than I had intended”* (Kwon et al. 2013). However, these scales concern themselves with a person’s experiences and worries towards their smartphone use, rather than actual usage time or frequencies (Elhai, Dvorak, Levine, & Hall, 2017). It is therefore problematic that often conclusion from studies using these scales advocate a reduction in overall smartphone time for wellbeing benefits, and conflate this idea of use with people’s appraisals of their use (see chapter 6 for a full discussion). Consequently, one of the aims of this chapter is to explore whether it is appropriate to use a problematic usage scale instead of measuring actual use when making conclusions regarding the time people spend on their devices. Further it is possible to assess ‘tolerance’ or ‘overuse’ by examining if actual time spent on the device relates to problematic usage scales.

This is in line with a general trend in social psychology, whereby since the 1970’s, there has been a rapid decrease in the number of studies which measure behaviour (Baumeister, Vohs, & Funder, 2007). Instead self-report measures and surveys prevail, partly due to the popularity of studying cognitions and perceptions (Baumeister et al., 2007; Doliński, 2018). It is important to note that in some cases, self-report measures are appropriate, in particular, when trying to capture aspects of human experience. However, self-reports may not be suitable when documenting the frequency and time people spend on their devices. Specifically, when estimating smartphone use, this places a high cognitive burden on the participant, occurring when people attempt to recall behaviours that they do not typically think about or record on a regular basis (Boase & Ling, 2013). Notably 50% of all mobile phone uses (unlock to lock) has been found to be under 30 seconds in duration (Yan, Chu, Ganesan, Kansal, & Liu, 2012). As a large amount of smartphone interactivity consists of many short bursts of use, any subjective estimate is likely to ignore rapid, yet pervasive, checking behaviours (Oulasvirta, Rattenbury, Ma, & Raita, 2012). Consequently, self-report measures of technology use are expected to have some errors.

The size and direction of these errors will be explored further in this chapter. For example, when participants are asked to estimate the length of a given duration, findings generally show a mismatch in participants’ recalled stimulus duration and the objective ‘actual’ length of time the stimulus was presented for (Grondin, 2001). This is often described as an overestimation or underestimation of duration length and has established that the experience of time is not always objective (Grondin, 2008). This error has been explained by time perception models. The memory marker model posits that everyday occasions are encoded as a series of events or markers (Ahn, Liu, & Soman, 2009). Events which involve numerous contextual changes (i.e. a variety of tasks) will feel like it is going quicker in the present but be seen as lasting longer after a delay (Ahn et al., 2009). When applying this theory to recalling smartphone use, greater switching between applications or screen on/off behaviours could distort people's perceptions of how long they spent on their device. Furthermore, if smartphone use becomes habitual and requires less conscious processing over time, (see chapter two), this would likely affect the encoding of events in memory and distort time estimation. Of relevance, recent work using psychometric scales has shown that those who report using their phone in greater amounts tended to use their phone more absentmindedly (Marty-Dugas et al., 2018). Thus, it can be predicted that heavier smartphone users will make greater estimation errors.

If self-reports are likely to produce inaccurate results when measuring smartphone use, what alternative methods can be explored moving forward? It has been proposed that the 'gold standard' way of measuring smartphone use is to gather activity logs directly from the device itself (Boase & Ling, 2013). This methodology is predominately used in computer science, whereby researchers develop mobile applications that logs smartphone screen states, calls, foreground application and other digital traces of activity (Aharony, Pan, Ip, Khayal, & Pentland, 2011; Piwek, Ellis, & Andrews, 2016). Thus, a participant's smartphone can be a research tool to gather data about how they use their device. It has been speculated that this 'objective' method has not reached popularity in psychology due to barriers such as programming skills, security requirements and privacy considerations (Piwek et al., 2016). However, in recent years, frameworks have been developed which provide 'out-of-the box' solutions when creating smartphone applications, that do not require programming skills, and can be used without dependence on software developers (Aharony et al., 2011; Piwek et al., 2016). In addition, companies which manufacture smartphones are starting to provide their own tools which allow users to manage and see their smartphone usage (Apple, 2018). This has made it more accessible for researchers to directly document a person's usage patterns.

Having available an 'objective' measure of smartphone use makes it possible to compare actual use and self-report measures. Consequently, the criterion validity of self-reports can be assessed by investigating how well these predict actual smartphone use. Currently, only a handful of studies exist which compare actual smartphone behaviours to self-reports, and they predominantly focus on phone calls and text messages, rather than general phone use. On a nationally representative Norwegian sample of 1382 respondents, Boase & Ling (2013) asked people to estimate the frequency of outgoing calls and text messages that occurred 'yesterday'. Findings showed large correlations between self-reports and actual logs of text messages (r = .58) and calls (r = .55) with a general trend to over-report these behaviours (Boase & Ling, 2013). Through accessing records from U.K. mobile network providers, medium-to-large relationships were found between actual and self-reported number of weekly outgoing calls (r = .48) and weekly total call durations (r = .60) (Parslow, Hepworth, & McKinney, 2003). This finding was mirrored in a different sample when measuring estimated vs. actual daily outgoing calls (r = .46) and daily incoming calls (r = .50), with a general trend to over-report both behaviours (Kobayashi & Boase, 2012). Finally, mobile phone calls of 672 volunteers were recorded by phone operators in 11 different countries (Vrijheid et al., 2006). Correlations between estimated and actual monthly phone calls were large, ranging between .5 to .8 across countries (Vrijheid et al., 2006). Those who underestimated were light users and those who overestimated were heavy users (Vrijheid et al., 2006). Thus, when examining phone calls and text messages, studies reliably find errors in people's usage estimates. Notably, across studies, effect sizes should be higher if two measures are operationalising the same concept equally well, showing at least effect sizes r > .7 (Boase & Ling, 2013; Carlson & Herdman, 2012).

This chapter aims to advance on previous studies by exploring several outstanding research questions. Firstly, the chapter explores whether a large correlation exists between general objective smartphone use, such as smartphone screen time and overall smartphone activity when compared to estimates. Notably, only one previous study has examined this on a small sample of college students (n = 35) (Lee, Ahn, Nguyen, Choi, & Kim, 2017). As expected, students underestimated their daily durations of general smartphone use by 20% with a mean correlation of r = .52 between reported and measured use (Lee et al., 2017). Therefore, the reliability of Lee et al., (2017) findings will be explored on a larger sample and across both iPhone and Android users.

Secondly, the relationship between estimated and actual frequency of use, which is likely to be mis-reported, is still to be explored. Measuring the number of smartphone pickups (aka total number of uses) is one way to examine this relationship, however investigating what actually constitutes as a smartphone 'check', (aka quick or rapid use) can contribute to a new behavioural definition and advance our understanding of smartphone usage norms. This is important given a large amount of smartphone interactivity consists of many short bursts of use, and studies to date are yet to explore whether estimates of these rapid checking behaviours are accurate (Yan, Chu, Ganesan, Kansal, & Liu, 2012; Oulasvirta, Rattenbury, Ma, & Raita, 2012). Thirdly, as psychometric scales are increasing in popularity (Ellis, 2019), whether these can be a proxy for actual phone usage needs assessing. Notably, study one outlines the first study to date which attempts to validate psychometrics instruments developed to measure smartphone use against actual behaviour. Finally, exploring how long researchers need to track a person's smartphone behaviours for, in order for this data to be representative of their overall use, will be examined. Consequently, the assessment of these additional research questions, will create a more informed understanding on how to reliably, and validly measure smartphone usage behaviours.

This chapter will address these aims across two studies. The first study consists of an online survey which examines the relationship between 'Apple Screen Time' data and self-reported daily pickups, screen-time, and several psychometric smartphone usage scales across a representative sample. The second study involves the development of an Android application using programming frameworks to capture second by second smartphone activity over a two-week period. Here, what constitutes as a 'smartphone check' is explored, with further analysis of how 'actual' smartphone checks relate to estimated daily checks. Effect size benchmarks are defined in this chapter as small ($r >.1$) medium ($r >.3$) and large ($r >.5$) respectively, in line with existing recommendations (Cohen, 1988; Cohen, 1992), and adopts a $r >.7$ benchmark when ascertaining if self-reports can be a proxy for objective usage (Carlson & Herdman, 2012). The review of the literature described above allows for several predictions to be made:

Hypothesis one: There will be a large positive correlation when estimating smartphone screen/activity time with actual usage time.

Hypothesis two: Participants will find it difficult to recall average daily pickups or checks. Therefore, small or no relationships will exist between estimated and actual daily checks/pickups.

Hypothesis three: The more a person uses their smartphone, the greater their estimation errors will be.

Hypothesis four: Psychometric scales which measure technology use can be used as a proxy for actual use. Therefore, correlation coefficients between actual use and scales should exceed .70.

4.2. Study one: Comparing objective smartphone data to psychometric scales.

4.2.1. Method

4.2.1.1. Participants

An online survey received 431 responses. However, after the removal of those who were part completers, had missing values, who had synchronised ‘Apple Screen Time’ with their iPad, none consenters, did not have iOS 12, or an iPhone 5, the final sample consisted of 223 participants. 124 were women, and 99 were men. Participants were on average 31.53 years old (*SD* = 11.08). Recruitment took place via Prolific Academic, an online subject pool system which pays participants to take part in research studies. Therefore, the study had access to a large pool of participants, and those who took part were paid (£5.34/hr) for their time.

4.2.1.2. Measures

Ten scales were chosen to be compared to actual smartphone usage. The selection below contains the most highly cited smartphone addiction scale (Kwon et al., 2013), those which capture nomophobia (the fear of being out of mobile phone contact) (Yildirim & Correia, 2015), addiction to smartphone applications (Csibi, Griffiths, Cook, Demetrovics, & Szabo, 2018), smartphone’s importance to self-identity (Sivadas & Venkatesh, 1995), absent-minded use (Marty-Dugas et al., 2018), general use (Marty-Dugas et al., 2018; Rosen, Whaling, Carrier, Cheever, & Rokkum, 2013), smartphone attachment (Sivadas & Venkatesh, 1995) and problematic use (Bianchi & Phillips, 2005; Lopez-Fernandez et al., 2018). A variety of scales were screened in the current study, instead of just assessing one, as this may have led to spurious results due to the characteristics of a particular scale/topic.

4.2.1.3. Scales

The Extended Self Scale (ESS) measured the extent to which a person's smartphone had been incorporated into an individual's self-identity (Sivadas & Venkatesh, 1995). The scale contained six questions such as *"My _ helps me achieve the identity I want to have"* and participants responded on a seven-point Likert-scale ranging from *"Strongly Disagree"* (1) to *"Strongly Agree"* (7). In this study, the blank space within each question was filled with the word *"Smartphone"*. Total scores could range from 6 to 42, whereby high scores indicated larger incorporation of the specified object into the extended self. This scale had good internal reliability ($\alpha = .93$).

The Attachment Scale (ATS) contained four questions which measured how attached a person was to their smartphone (Sivadas & Venkatesh, 1995). Like the extended self scale, the questions contained blank spaces e.g., *"I am emotionally attached to my _"* which were filled here with the word *"Smartphone"*. Participants responded on a seven-point Likert-scale ranging from *"Strongly Disagree"* (1) to *"Strongly Agree"* (7) and total scores could range from 4 to 28. Higher scores indicated higher attachment to the specific object. This scale had good internal reliability ($\alpha = .87$).

The Mobile Phone Problem Use Scale (MPPUS) contained 27 questions which measured issues with smartphone use such as tolerance, craving, negative life consequences in the areas of social, familial, work, and financial difficulties (Bianchi & Phillips, 2005). Participants responded to questions such as, *"I lose sleep due to the time I spend on my mobile phone"* on a ten-point Likert-scale ranging from *"Not true* *at all"* (1) to *"Extremely True"* (10). Total scores could range from 27 – 270. This scale had high internal reliability ($\alpha = .93$)

The Nomophobia Questionnaire (Nom) contained 20 questions which measured a person's anxieties and fears towards being away from their smartphones (Yildirim & Correia, 2015). All items were rated on a seven-point Likert-scale ranging from *"Strongly Disagree"* (1) and *"Strongly Agree"* (7). Participants were asked to rate how much they agreed to statements such as *"If I were to run out of credits or hit my monthly data limit, I would panic"*. Total scores could range from 20 to 140. Scores equivalent to 20 suggested an absence of nomophobia, 20-60 indicated mild nomophobia, 60-100 indicated moderate nomophobia and >100 indicated severe nomophobia. This scale had high internal reliability ($\alpha = .95$).

Smartphone addiction was measured using the Smartphone Addiction Scale (SAS) which contained 33 items (Kwon et al., 2013). Participants rated the extent to which they agreed to several statements, for example *"Feeling pleasant or excited while using a smartphone"*. Participants responded on a six-point Likert-scale ranging from *"Strongly Agree"* (1) and *"Strongly Disagree"* (6). Total scores could range from 33 – 198. This scale had high internal reliability ($\alpha = .95$) and higher scores indicated more serious smartphone addiction.

The Smartphone Application-Based Addiction Scale (SABAS) measured the risk of addiction towards smartphones and their applications (Csibi, Griffiths, Cook, Demetrovics, & Szabo, 2018). The scale consisted of six questions such as *"My smartphone is the most important thing in my life"* and participants responded on a six-point Likert-style scale ranging from *"Strongly Disagree"* (1) to *"Strongly Agree"* (6). Total scores could range from 6 – 36. This scale had high internal reliability (α = .81) and higher scores indicated greater addiction.

The Short Version of the Problematic Mobile Phone Use Questionnaire (PMPUQ-SV) was made up of 15 questions which measured problematic smartphone use, including using smartphones when prohibited (Lopez-Fernandez et al., 2018). Participants rated how much they agreed with statements such as *"Its easy for me to spend all day not using my phone"* on a four-point Likert-scale ranging from *"Strongly agree"* (1) to *"Strongly disagree"* (4). Overall scores could range from 15 to 60 with higher scores indicating greater problems due to mobile phone use. This scale had high internal reliability (α = .78).

The nine-item smartphone subscale from the Media and Technology Usage and Attitudes Scale (MTUAS), was used to measure general smartphone usage (Rosen et al., 2013). Participants were asked to indicate how often they engaged with specific activities on their mobile phone such as *"Get directions or use GPS on a mobile phone"* and respond on a ten-point Likert-scale ranging from *"Never"* (1) to *"All the time"* (10). Means were used to create an overall score between 1 and 10. Higher scores indicated greater general smartphone use. This scale had high internal reliability (α = .82)

The Smartphone Use Questionnaire – General (SUQ-G), was used to measure the frequency in which people engaged in a broad range of general smartphone related behaviours (Marty-Dugas et al., 2018). Participants responded to 10 questions based on a typical day such as *"How frequently do you send and receive text messages or e-mails?"*. Responses were recorded on a seven-point Likert-scale ranging from *"Never"* (1), to *"All the time"* (7). Means were used to create an overall score between one and seven and higher scores indicated that a person used their phone more frequently. This scale had high internal reliability (α = .76)

The Smartphone Use Questionnaire – Absent Minded (SUQ-A), was used to measure the frequency in which individuals engaged with their phones in an absent-minded manner (Marty-Dugas et al., 2018). Participants responded to ten questions based on a typical day such as *"How frequently do you send and receive text messages or e-mails?"*. Responses were recorded on a seven-point Likert-scale ranging from *"Never"* (1), to *"All the time"* (7). Means were used to create an overall score between one and seven and higher scores indicated that a person used their phone more absent-mindedly. This scale had high internal reliability (α = .95)

4.2.1.4. Estimates of smartphone use

To measure estimates of their daily smartphone screen time, participants were asked one question: *"Please estimate how many hours and minutes you spend on your phone each day"*. Participants gave two responses to this question; hours and minutes. To measure estimates of how many times a day they 'picked up' their device, they were asked: *"Please estimate how many times a day you pick up and use your phone"*. Participants gave one numerical response to this question.

4.2.1.5. Objective smartphone use

'Apple Screen Time' is a new feature that resides in iPhones that are updated to iOS 12 and are of the model 5 or later (Apple, 2018). Smartphone usage logs can be accessed by visiting the settings in a person's iPhone. When selecting the seven-day view, data from the past week is displayed in several interactive bar charts that can be extracted by pressing on the bars. 'Actual screen time' was measured by asking people to document their daily screen time statistics reported by 'Apple Screen Time' for the past week. 'Actual pickups' (total number of uses) was measured by asking people to document their daily pickups statistics reported by 'Apple Screen Time' for the past week.

4.2.1.6. Procedure

After using the link to access the online questionnaire, participants were presented with study information and a digital consent form. If participants agreed to take part, they were then asked to estimate how many hours and minutes they spent on their phone each day. In addition, participants were also asked to estimate how many times a day they picked up and used their phone. Afterwards, participants went through a series of checks whereby they were asked if they had an iPhone five or later and whether they had iOS 12 installed. They were further asked if they had seven days' worth of screen time data in the 'Apple Screen Time' settings. If they answered no to the final two questions, they were asked to return to the study in seven days after updating to the latest OS and after seven days' worth of screen time data had been collected by their device. Participants were also asked if they owned an iPad and whether they had synced screen time across both devices.

If all of the above checks came back satisfactory, participants were then asked to complete the ten smartphone usage scales; ESS, ATS, MPPUS, Nom, SAS, SABAS, PMPUQ-SV, MTUAS, SUQ-G, and the SUQ-A. The scales were presented in a randomised order to each person to control for any order effects. Then participants were directed to visit the screen time settings in their iPhone and prompted to go on the seven-day view. They were then asked to indicate which day of the week corresponded to the first (column furthest to the left) day in their screen time settings. Participants were then asked to press down on the bars in the screen time graph and record each days' screen time in hours and minutes. This was then replicated in the pickups graph whereby; participants were asked to press down on the bars and record the number of pickups for each day. Finally, participants were asked to report their age and gender. Finally, they were presented with a debrief and thanked for their time.

4.2.1.7. Ethics

All procedures received ethical approval and complied with the British Psychological Societies ethics guidelines for internet-mediated research (Hewson et al., 2013). Participants were given a unique ID upon clicking the survey link so that all responses remained anonymous. No deception took place in this study. Hence, the full aims of the project were provided in the study information. Participants were also asked to provide digital consent and were not financially penalised for deciding not to take part. At any time, participants could withdraw from the study by closing the survey and emailing the researcher with their unique participant ID or their prolific ID. Again, doing so would not impact their financial reward. Participants were also given the option of withdrawing for up to two weeks after they completed the study. At the end of the survey, a debrief was provided, reiterating their unique participant ID and contact details of the researcher if they had any further questions or issues.

4.2.2. Results

4.2.2.1. Analysis Plan

Initially, the analysis describes how scores for each of the smartphone usage scales were calculated. Following, is a description of how the objective smartphone data and estimates were processed and formulated into variables for the analysis. In addition, tests of normality were conducted to decide whether none parametric correlations should be performed in the analysis, alongside other statistical procedures. Next, estimates of daily smartphone screen time and pickups were compared to actual usage data. The size and direction of any estimation errors were then calculated to understand whether increased smartphone use led to greater estimation errors. Actual usage data was then compared to smartphone usage scales to examine their validity against objective measures.

4.2.2.2. Scoring

Scores for the extended self scale, the mobile phone problem use scale, the nomophobia questionnaire, the smartphone addiction scale, and the smartphone application-based addiction scale were created by adding all responses together to create a total score for each scale. The attachment scale and the shortened version of the problematic mobile phone use questionnaire required some reverse coding, and once completed, responses were summed to create a total score for each scale. To create scores for the smartphone subscale from the media and technology usage and attitudes scale, the smartphone use questionnaire – general, and the smartphone use questionnaire – absent minded, responses on each scale were averaged to create a mean score.

4.2.2.3. Smartphone Variables

Hours and minutes were reported separately in two different responses when gathering daily smartphone screen time data from the 'Apple Screen Time' settings. To combine and create one screen time variable for each of the seven days, minutes was converted into a decimal as follows: minutes/60. This decimal was then added to the 'hours' response, to get a complete screen time measure (in hours) for each day. An average daily screen time statistic was then computed per person by taking the daily amount of screen time from the first six days and then calculating the mean. Six rather than seven days were used to compute this mean, as data from the seventh day did not represent a full day. In a similar manner, an average daily pickups statistic was calculated per person by taking the daily number of pickups from the first six days and then calculating the mean.

Estimated average daily screen time was also collected in two different responses: one for hours and one for minutes. Matching the calculations conducted for actual screen time, both these responses were combined to create an estimated value (in hours) for the analysis. Raw estimated number of daily pickups were used in the analysis. Thus, no manipulation was performed on this data.

Table 4.1. Descriptive statistics of all variables measured in the study, including summaries for smartphone scales, estimated and actual use (n = 223).

Variable	*M*	*SD*	Range	α	Number of items
Extended Self Scale	21.08	8.93	6 - 42	.93	6
The Attachment Scale	17.07	6	4 - 28	.87	4
Mobile Phone Problem Use Scale	108	40.79	27 - 242	.93	27
Nomophobia Questionnaire	82.11	25.48	27 - 140	.95	20
Smartphone Addiction Scale	92.43	29.15	33 - 177	.95	33
Smartphone Application-Based Addiction Scale	15.60	5.85	6 - 33	.81	6
Short Version of the Problematic Mobile Phone Use Questionnaire	33.01	8.58	17 - 59	.78	15
Media and Technology Usage and Attitudes Scale	6.20	1.29	2.22 - 10	.82	9
Smartphone Use Questionnaire – General	4.80	0.87	2.3 – 6.8	.76	10
Smartphone Use Questionnaire – Absent Minded	4.51	1.45	1 - 7	.95	10
Estimated average daily screen time	3.82	2.36	0.33 – 18.67	-	1
Estimated number of daily pickups	44.68	38.07	3 - 300	-	1
Average Daily Screen Time	3.93	2.09	0.27 – 13.44	.93	7
Average Daily Pickups	88.91	66.37	2.17 – 650.5	.95	7

4.2.2.4. Normality Tests

Scores from the smartphone addiction scale conformed to a normal distribution when conducting Shapiro-Wilks tests [W = 0.99, p = .10]. However, the rest of the 13 variables listed in Table 4.1. had distributions which were significantly different from a normal distribution (all p's <.05). As such we followed Bishara and Hittner (2017) recommendations and conducted Spearman's correlations with Fieller, Hartley and Pearsons (1957) variance when calculating 95 % confidence intervals as these are robust against non-normality.

4.2.2.5. Validity of estimate measures

To begin, it was of interest to assess whether people could accurately report the daily amount of time they normally spent on their smartphone. To do this, Spearman's correlations were conducted between estimated and actual average daily screen time. Findings showed a large positive correlation between estimated and actual screen time [$\boxed{r_s}$ (221) = .56, p <.001, 95% CI = 0.46, 0.65]. It was also of relevance to examine whether people could accurately report the frequency in which they use their smartphone on a daily basis. Therefore, Spearman's correlations were conducted between estimated and actual daily pickups. A medium positive correlation was found between estimated and actual pickups [$\boxed{r_s}$ (221) = .40, p <.001, 95% CI = 0.28, 0.51]. Consequently, people can estimate to some degree how much they use their smartphone.

To understand how people's estimates deviated from actual usage, two new variables were created. Average daily screen time was subtracted from estimated daily screen time to create a variable which documented the size of people's estimation errors. In a similar manner, average daily pickups were also subtracted from estimated daily pickups in order to create a pickups error variable. Summary statistics showed that 130 people (58.3 %) underestimated their screen time, whereas 93 people (41.7%) overestimated their screen time. However, when examining the errors in estimating pickups, participants largely underestimated their daily smartphone uses, as 193 people (86.5%) underestimated their daily pickups, whereby 30 (13.5%) overestimated.

It was then possible to explore if the amount of objective usage, such as the frequency of pickups or time spent using smartphones, predicted the size of the errors people made. To assess this, Spearman's correlations were firstly conducted between screen time estimation error with average daily screen time, and secondly between pickups estimation error and average daily pickups. Results further showed a significant negative correlation between screen time estimation error and average daily screen time [r_s (221) = -0.44, p <.001, 95% *CI* = -0.55, -0.38]. Once plotted (see Fig. 4.1.) this indicated that people who spent a lot of time on their smartphone, tended to underestimate how long they spent on their phone, and people who spent a little time on their smartphone tended to overestimate. There was also a significant and large negative correlation between pickups estimation error and average daily pickups [r_s (221) = -0.79, p <.001, 95% *CI* = -0.83, -0.73]. When looking at the plot (see Fig. 4.1.), those who 'picked up' their phone a lot made proportionally much greater underestimation errors than those who 'picked up' their phone a little.

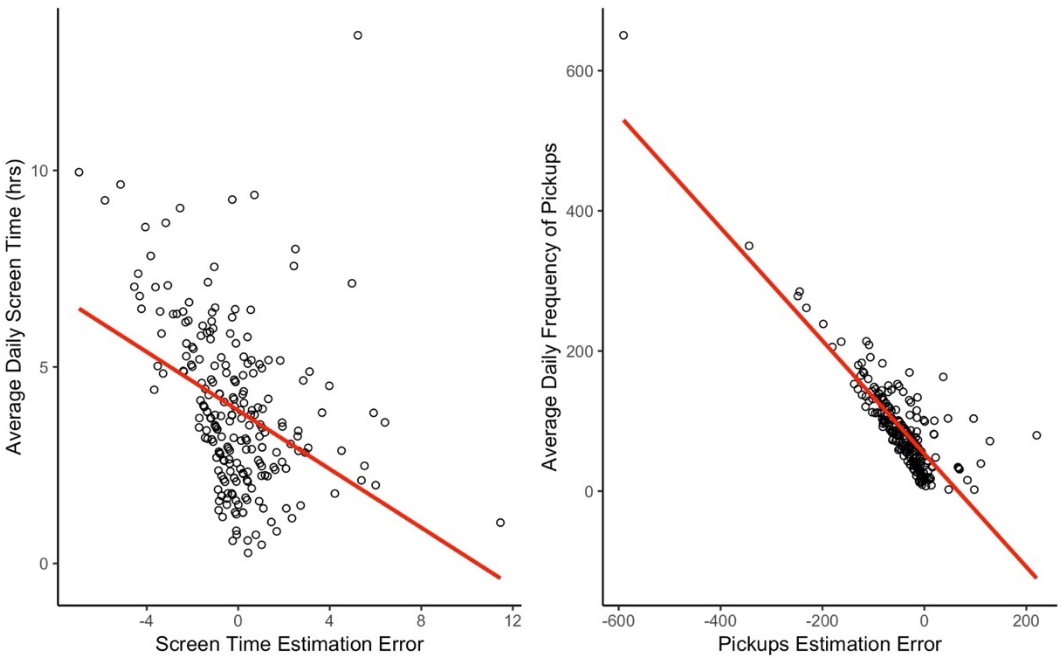

Figure 4.1. Graphs showing negative correlations between the errors people made when estimating use and data from actual use for both screen time and pickups measures. Regression line between the two variables is plotted in red.

4.2.2.6. Validity of smartphone usage scales

To analyse the validity of smartphone usage scales, scores from each of the scales were compared to average daily screen time and average daily pickups. This was done using Spearman's correlations. All smartphone scales significantly positively correlated with average daily screen time (all *p*'s <.05). However, effect sizes only ranged between r_s = .23 and r_s = .42 with an average effect size of r_s = .34. When examining average daily pickups, all scales apart from extended self scale significantly and positively correlated with average daily pickups. However, effect sizes from the pickups analysis were even smaller, ranging from r_s = .01 to r_s = .33, with an average of r_s = .21. If two variables were measuring the same phenomena, it would be expected that large effect sizes (r >.7) would occur between them (Carlson & Herdman, 2012). Therefore, smartphone usage scales lack validity if used as proxy for actual smartphone usage.

Table 4.2. Spearman's correlations between each of the scales and average daily screen time, with 95% confidence intervals (n = 233).

	Spearman's Correlations			
	BCa 95% *CI*	$\boxed{r_s}$	p	95% *CI*
Extended Self Scale	0.06, 0.32	.23	< .001	0.10, 0.35
The Attachment Scale	0.25, 0.45	.37	< .001	0.25, 0.48
Mobile Phone Problem Use Scale	0.23, 0.46	.36	< .001	0.24, 0.48
Nomophobia Questionnaire	0.21, 0.44	.33	< .001	0.20, 0.45
Smartphone Addiction Scale	0.25, 0.49	.42	< .001	0.30, 0.52
Smartphone Application-Based Addiction Scale	0.14, 0.39	.31	< .001	0.18, 0.43
Short Version of the Problematic Mobile Phone Use Questionnaire	0.16, 0.42	.30	< .001	0.17, 0.42
Media and Technology Usage and Attitudes Scale	0.16, 0.40	.31	< .001	0.18, 0.42
Smartphone Use Questionnaire – General	0.24, 0.46	.35	< .001	0.23, 0.47
Smartphone Use Questionnaire – Absent Minded	0.24, 0.44	.38	< .001	0.26, 0.49

Table 4.3. Spearman's correlations between each of the scales and average daily pickups, with 95% confidence intervals (n = 233).

	Spearman's Correlations			
	BCa 95% *CI*	$\boxed{r_s}$	p	95% *CI*
Extended Self Scale	-0.15, 0.13	.01	= .88	-0.13, 0.15
The Attachment Scale	0.05, 0.26	.16	< .05	0.03, 0.29
Mobile Phone Problem Use Scale	0.04, 0.26	.23	< .001	0.10, 0.36
Nomophobia Questionnaire	0.03, 0.25	.18	< .01	0.05, 0.31
Smartphone Addiction Scale	0.03, 0.29	.26	< .001	0.13, 0.38
Smartphone Application-Based Addiction Scale	-0.03, 0.22	.16	< .05	0.03, 0.29
Short Version of the Problematic Mobile Phone Use Questionnaire	-0.05, 0.20	.14	< .05	0.00, 0.27
Media and Technology Usage and Attitudes Scale	0.16, 0.36	.33	< .001	0.20, 0.44
Smartphone Use Questionnaire – General	0.18, 0.38	.31	< .001	0.19, 0.43
Smartphone Use Questionnaire – Absent Minded	0.14, 0.36	.33	< .001	0.21, 0.45

4.2.3. Study one: Summary

Study one is the first study to date which aimed to validate the increasing number of psychometric instruments which have been developed to capture technology related behaviours. Notably, asking participants to provide an estimate of their daily screen time had a stronger relationship with actual screen time than any psychometric scale. The same was found when examining the Spearman's correlations between estimated daily pickups and actual daily pickups, having a stronger relationship (r_s = .40) than the best performing psychometric scales (r_s = .33). If self-reports of technology use are to be collected, the results of this study suggest a single estimate is the superior measurement, requiring less burden on the participant to complete, alongside better criterion validity. Therefore, hypothesis four is rejected as psychometric scales cannot be used as a substitute for objective usage measures.

In line with predictions, a large positive correlation was found between estimated daily screen time and actual screen time, supporting hypothesis one. Previous studies have shown this on a sample of 35 students (Lee et al. 2017), and this has been replicated here on a more representative sample of over 200 people. A medium positive correlation was also found between estimated daily pickups and actual pickups, which is larger than predicted in hypothesis two.

When examining the errors people made, findings showed that people who spent a lot of time on their smartphone, tended to underestimate how long they spent on their phone, and people who spent little time on their smartphone tended to overestimate. Therefore, whilst increased smartphone use did increase estimation errors in line with hypothesis one, those who used their phone very little also made estimation errors in the opposite direction. Opposingly, the results for pickups were one-dimensional. Participants predominately underestimated how many times they used their phone a day including, a large negative correlation between increased number of pickups and underestimation. This supports the view that some pickups may have not been coded in memory (Ahn et al., 2009), or that some pickups occur due to absent-mindedness (Marty-Dugas et al., 2018), as people report less pickups than the actual number recorded.

Moving forward, it appears that habitual use may be a driving force behind the size of estimation errors. To further understand how any subjective estimate is likely to ignore rapid, yet pervasive, checking behaviours (Oulasvirta et al., 2012), it was important to look at objective smartphone use in higher resolution than was documented in study one. To elaborate, 'Apple Screen Time' only reports daily or hourly phone use statistics dependent on the 'tab' selected. However, it has been shown previously that 50% of all mobile phone uses (unlock to lock) has been found to be under 30 seconds in duration (Yan et al., 2012). Thus, to document habitual checking behaviours, and to get a greater understanding of how this may influence estimation errors, any measure of objective smartphone use needs to measure second-by-second usage. An Android application which had these capabilities was developed in study two. Additionally, it was of interest to see if findings were consistent of across users with a different smartphone OS, as these represent a separate sample with different demographics and personality traits (see chapter 3). Consequently, in study two, Android smartphone users were recruited. As a final point, study one had a limitation, whereby a person may have looked at their screen time statistics prior to completing their daily estimates, and this knowledge could have improved their estimation. Whilst the study attempted to control for this by having the estimation questions at the very beginning of the survey, and through running the study in the first couple of weeks after the global launch of the 'Apple Screen Time', study two addressed this limitation through utilising an application which gave the user no feedback on their usage.

4.3. Study two: Comparing objective smartphone data to estimates of use.

The purpose of study two was to address the limitations of study one, and to investigate the qualities of 'checking' behaviours, a variable which is distinct from 'pickups' and represents very quick phone uses. This was achieved through the development of an Android application which tracked second-by-second usage over a two-week period. By looking in detail at uses which were short in duration and through recording how long it took participants to 'check' a text message sent to their phone in the laboratory, it was possible to define what constitutes as a smartphone check. Subsequently, it was explored whether participants could estimate the frequency of these checks. To further investigate if smartphone use is habitual, the consistency of daily screen time, pickups and checks was assessed across the 13 days of the study.

4.3.1. Methods

4.3.1.1. Participants

Twenty-nine participants were recruited; however, two participants were excluded as they had technological problems partway through the study. This left 27 participants [17 female] between the ages of 19-33 in the sample (*M* = 22.52, *SD* = 4.68). This sample size was adequate when aiming to replicate findings from study one, as priori power analysis conducted in the software G*Power showed only 21 participants were required to find effect sizes ~.50 or more in correlation analysis when $\alpha = .05$ and power set to .8 (Faul, Erdfelder, Buchner, & Lang, 2009). All participants owned Android smartphones and consisted of staff and students from the University of Lincoln. The sample comprised clerical, technical, and academic university staff, and students who were studying a range of subjects, including psychology, computer science, zoology, and media production. All participants were reimbursed a small fee (£20) for their time. Participants were recruited via posters around the university campus, announcement on the staff intranet, and from the School of Psychology's subject pool system.

4.3.1.2. Measures

Phone use estimates

Estimated daily smartphone use was gathered by asking participants the question *"Please estimate how much time you think you spend on your phone in an average day including times when you are listening to music and chatting on the phone. So, this estimation involves everything you use your phone for"*. Participants were then asked to respond in two open-ended text boxes; one for hours and one for minutes. Estimated daily checks was assessed by asking participants the question *"How many* *times a day do you check your phone a day? Please write a number."* Participants then responded in an open-ended text box.

Smartphone usage application

An application was developed for Android based smartphones using FunF in a Box (Aharony et al., 2011). This was an online application generator which enabled researchers to create their own mobile sensing Android applications without programming skills. To create the application, the researcher connected their Dropbox account to FunF, and then ticked boxes indicating what data needed to be collected and selected from options concerning how the data should be uploaded. In the generator, the researcher also specified the text for the application's user interface. This was then submitted, and a few minutes later, the application's installer file (.apk) appeared in the researcher's Dropbox account. The on/off option was selected, resulting in a small application that records a timestamp when a smartphone use starts and ends. Usage refers to when the phone is in an interactive state (typically screen use, although this also includes processor intensive activities including calls and playing music). The application therefore simply recorded a timestamp when the phone became active, and a second when this interaction ended. This resulted in repeated on/off log data. Files containing this data were encrypted and uploaded to the server over Wi-Fi and then stored on the researcher's Dropbox account. Figure 4.2. shows the application user interface, describing the application's functionality, how to contact the researcher, and a button which if pressed would uninstall the application.

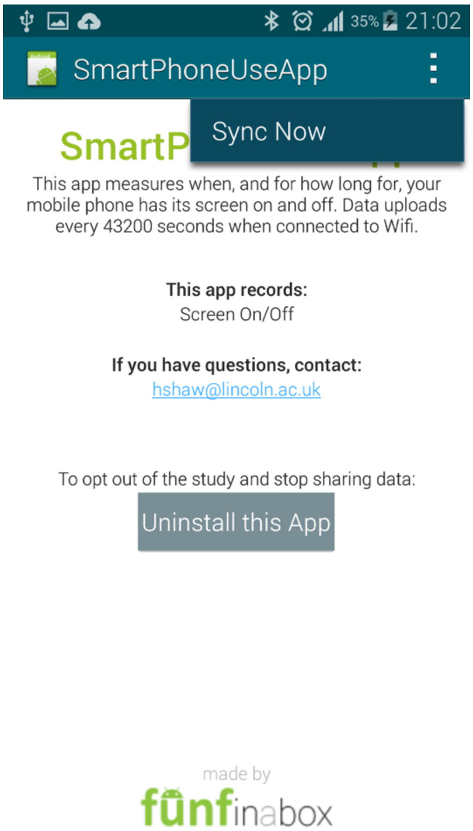

Figure 4.2. The general user interface for the 'Smartphone Usage Application' developed for study two.

Smartphone checking time

How long it took participants to check their smartphone was observed in a laboratory environment. The screens of participants' smartphones were switched off and then a text message was sent to their devices saying *"Hello, welcome to the experiment"*, which contained 33 characters. The researcher recorded how long it took participants to unlock their phone, read aloud the text message, and then lock their phone using a stopwatch. The researcher started timing when the smartphone elicited a message sound/blink and stopped timing when the phone was subsequently locked. The number of seconds displayed on the stopwatch was recorded.

Time estimation task

To get a general approximation of a participant's time estimating abilities, participants took part in a brief laboratory time-perception paradigm. Following the procedure of Wittmann, Leland, Churan, and Paulus, (2007), participants were asked to estimate temporal intervals lasting for 53 seconds. The beginning of the interval was indicated by the sound of a person saying *"start"*. The end of the interval was indicated by an alarm. Participants were asked not to count the seconds in their heads, but instead to estimate how much time they felt had gone by (see Fig. 4.3.) Participants were then asked to report their duration estimation by moving a virtual bar across a scale that spanned from 0 to 3 minutes. This task was completed twice in two different conditions. The first condition required participants to fixate on the screen during the time interval, whilst the second condition instructed participants to use their phone during the time interval. The order in which participants completed these conditions was randomised across participants to remove the influence of order effects. The test was administered using Inquisit, an online experimental environment. (see Fig. 4.3.)

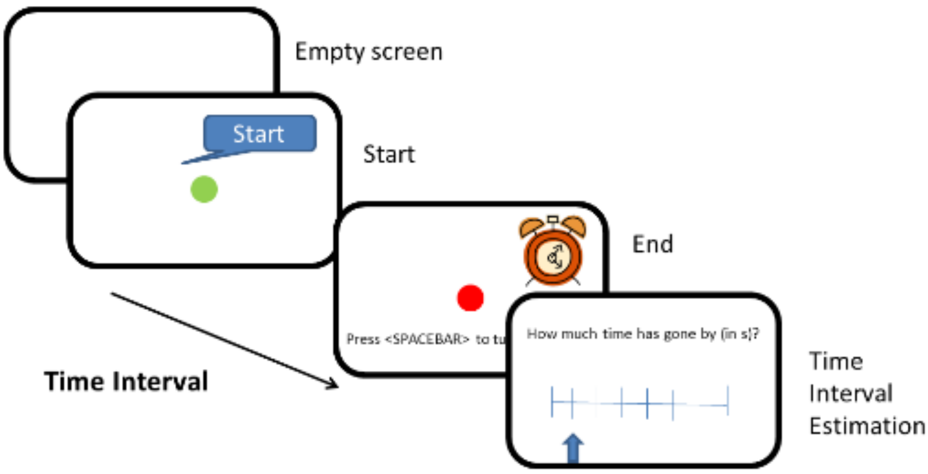

Figure 4.3. Illustration of the time estimation task given to participants.

4.3.1.3. Procedures

Participants who responded to advertisements or signed up via the SONA system were invited to the lab for day one of the study. In this session, participants were sat in front of a computer, and presented with study information. This included details of what the application did and did not record, the itinerary of each day of the study, and how the smartphone data from the application was stored and transferred to the researcher. Participants were also shown example data that was collected during piloting. Afterwards participants completed a digital consent form hosted on Qualtrics (an online survey provider), by responding to a 'yes/no' multiple choice question concerning whether they agreed to take part or not. Participants were then asked some further questions including their age, gender, mobile phone number, occupation, times when their phone is normally switched off, and any anticipated times this may happen over the two weeks.

Afterwards, participants took part in the time estimation task whereby they estimated the duration of a 53 second period in two conditions. In the first condition, participants fixated on the computer screen during the time interval and in the second condition, they used their smartphone during the time interval. Following, participants took part in the smartphone checking task. In this task, participants were sent a text message and asked to open their phone and read this text message aloud.

After, participants were asked to present their smartphone to the researcher so they could check if it had a file explorer application built in. If not, one was downloaded from the Google Play Store. This was needed as the application was installed on participants' smartphones by connecting their device to the researcher's laptop and dragging the applications' installer file (.apk) into a folder on their smartphone. Once transferred, clicking on this file initiated the installation of the application. Subsequently, the application appeared in the smartphones' list of installed applications, and once opened, asked the participant if they were happy for data collection to commence. Then participants were shown how to synchronise the data collected from the application to the online server. The researcher would receive a notification in response to a successful sync containing their FunF ID which was recorded. The time of this first sync was also written down. Lastly, on day one, the .apk file was removed from participants smartphones, and participants were instructed to synchronise their data each evening across the next two weeks. On days two to fourteen, participants used their phone as normal and recorded any instances where their phone had lost battery and/or was switched off.

On day 15, participants returned to the lab and were asked to estimate how much they used their phone on average each day (including calls and listening to music) over the last two weeks. They were then asked to estimate how many times they checked their phone each day over the last two weeks. This was collected using Qualtrics, and further questions were asked such as date of birth, the make, model, and age of their smartphone, whether they used their phone as an alarm clock, and questions regarding when their phone was switched off over the last two weeks. Then participants were asked to perform one final sync of the smartphone usage application data before uninstalling. Finally, participants were then debriefed, shown a graph of their smartphone use (see Fig 4.4), and were provided with participant payment.

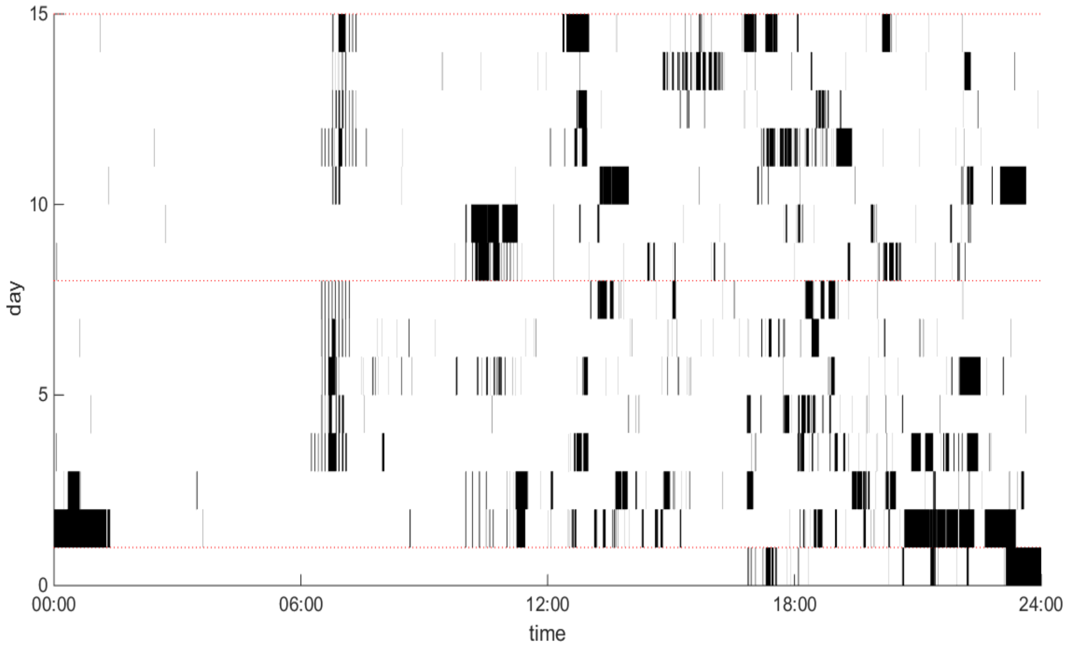

Figure 4.4. Graph showing one participant's smartphone usage. The Y axis displays the day of the study and the X axis shows time of day. Black lines indicate when the smartphone was in use.

4.3.1.4. Ethics

Approval for the project was obtained from the School of Psychology Research Ethics Committee at the University of Lincoln and all procedures complied the with the BPS code of conduct (British Psychological Society, 2018). All participants provided digital informed consent after being advised of the purpose of the study, and the type of data being collected. Participants were told the full aims of the study on day one and these aims were reiterated to participants during the debrief on day 14. Participants raw phone use files were encrypted for security purposes. In case of data upload issues from the smartphone usage application, the researcher had participants mobile phone numbers, which were linked to their FunF ID's. Participant's agreed prior to consenting to the lack of anonymity at this stage. However, once data collection was completed, the analysis was conducted using anonymous participant ID's. Participants could withdraw from the study at any time during the two weeks by uninstalling the application and emailing the researcher. Participants were further allowed to withdraw for up to two weeks after the study had finished.

4.3.2. Results

Data for this study is available online. See Ellis, Shaw and Wilcockson, (2018) and Andrews, et al. (2015).

4.3.2.1. Analysis Plan

First a description of smartphone behaviours captured by the smartphone application were documented by conducting descriptive statistics on the smartphone log data. Notably, what constitutes as a smartphone check was established. Afterwards, the analysis described how daily smartphone variables were derived from the objective log data. This was then used in the following analysis to understand how people's daily estimated checks and usage time compared to actual usage. The size and direction of any estimation errors was then calculated to see if this was related to people's performance on the time estimation task conducted in the lab. Finally, exploratory analysis established how many days of log data are required to be collected by researchers in order for their data to represent a person's overall smartphone use.

4.3.2.2. Smartphone Usage Descriptive Statistics

The majority of participants installed the application on a Thursday ($n = 14$) or Friday ($n = 12$) with a single installation occurring on a Wednesday. For all participants, the application was installed part way through day one and uninstalled part way through day 14. Consequently, only data from days 2-13 were included in the analysis to ensure only days with a full 24-hour worth of usage logs were examined. 32615 individual smartphone uses were recorded across all 13 days and participants. Within this, 54.86% of uses were under 30 seconds in duration and 42.50% were under 15 seconds. Thus, smartphone use was highly skewed (see Fig. 4.5). When plotting the frequency of uses which lasted a specified duration, distinct peaks of use occurred at 1 second, 2 seconds, 5 seconds, 10 seconds, and 30 seconds (see Fig. 4.5. and Fig. 4.6). These may represent specific checking behaviours, with the exception of the 30 second peak which represents a common screensaver duration. In accordance, analysis of smartphone screensavers showed that the median time it took smartphone screens to naturally turn off if the phone was locked was 30 seconds, and the median time when the smartphone was unlocked was 61 seconds. Also, in the laboratory, it took participants on average 8.42 seconds (*SD* = 1.53) to read a 33-character text message. Therefore, in a more natural environment, when not explicitly timed, the ten second peak could represent a message check. As these distinct peaks of use join the natural tail of the histogram at around 15 seconds (see Fig. 4.5.), and due to no distinct peaks of use occurring in any longer durations, it is possible to define a smartphone check as any use under 15 seconds long.

Daily smartphone data was then extracted using scripts from Andrews et al. (2015) which were specifically designed to create descriptive statistics from smartphone data collected using the FunF framework. Daily hours of smartphone activity, individual pickups, and checks (any use under 15 seconds) were extracted for each 24-hour time period (00:00-24:00) for each participant. Median daily hours of use were derived by taking the daily 'on' time in hours from days 2-13 individually, and then using these values to calculate a median per person. Similarly, the frequency of pickups and checks were extracted individually for each full day, which were then averaged to create a mean frequency of daily pickups and checks per person. On average, the 27 participants used their phone for 4.47 hours a day, picked up their phone 92.92 times a day, and checked their phone 39.96 times a day.

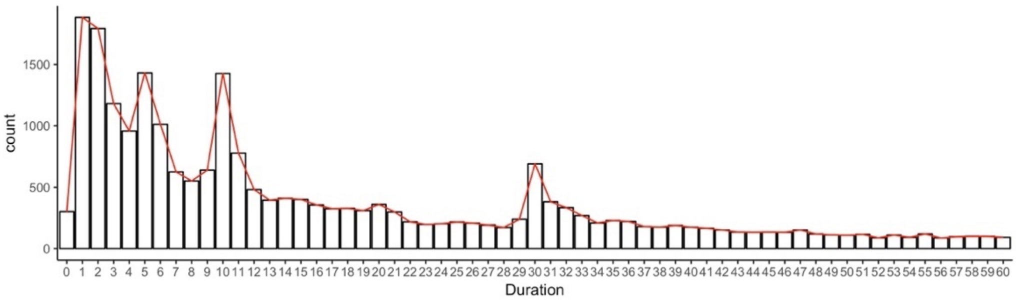

Figure 4.5. A graph showing the frequency of uses that lasted between 0 and 60 seconds in 1 second bins across all days and participants.

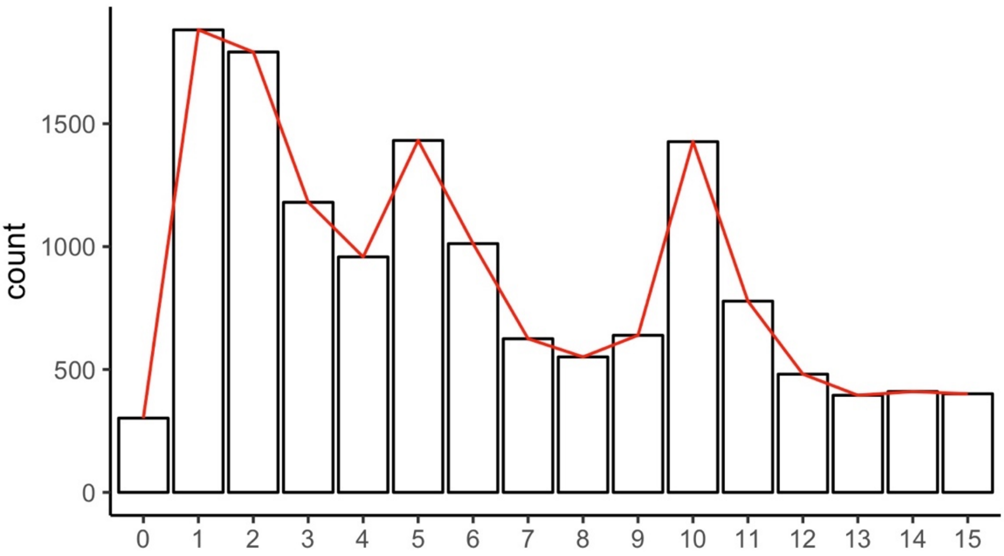

Figure 4.6. A graph showing the frequency of uses that lasted between 0 and 15 seconds in 1 second bins across all days and participants.

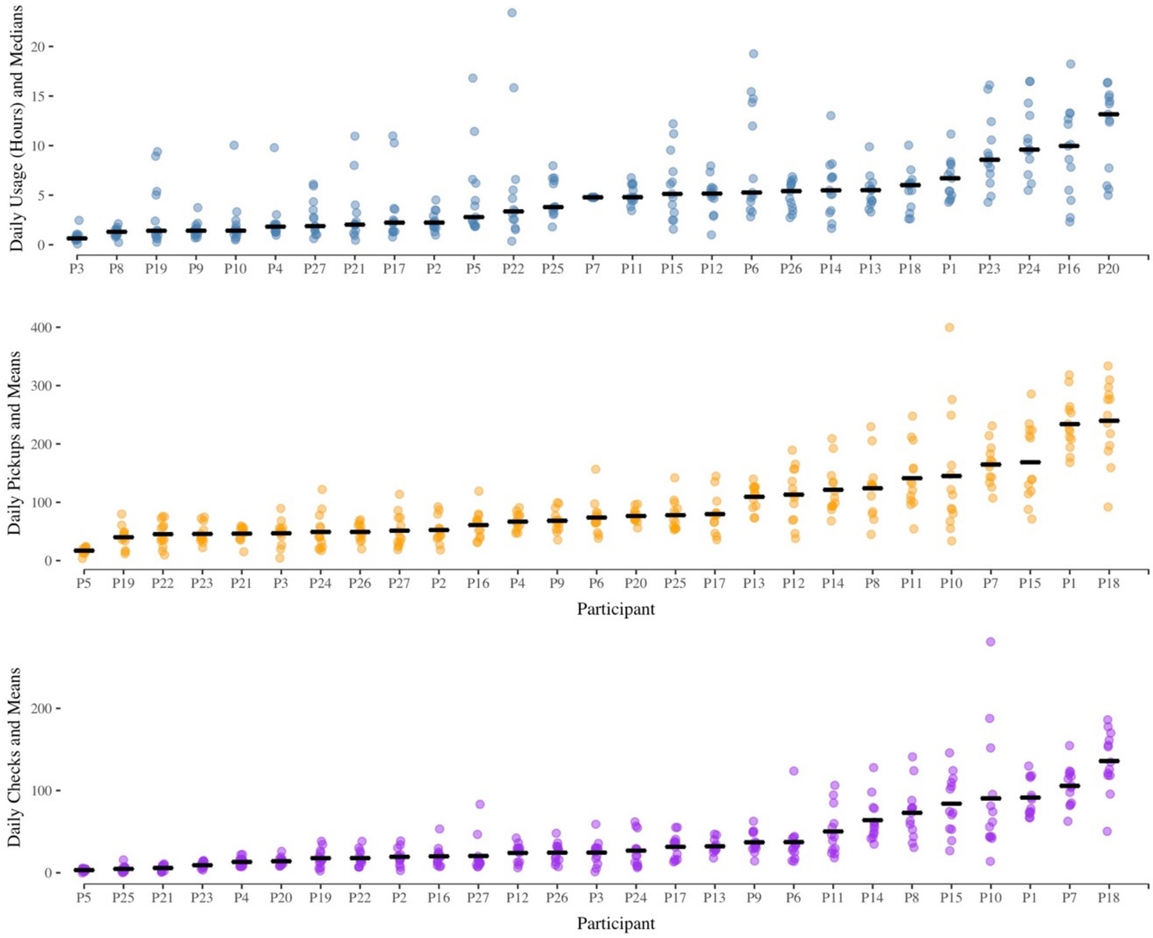

Figure 4.7. Plot showing individual participants' daily hours of smartphone use, checking behaviours and pickups for each of the 13 days. The top figure represents hours of use, followed by daily pickups and daily checks. The relevant measure of central tendency is also plotted for each person across the plots. Medians were used for hours of use and means for daily pickups and daily checks.

4.3.2.3. Estimated vs actual usage analysis

To compare whether people's estimates of their device use was in-line with their actual use, 24 participants who reported their perceived average daily phone use in hours and checks were examined in the following analysis. Resembling study one, correlations were conducted between estimates of use and actual use. As the distribution of smartphone usage durations is positively skewed (see Fig. 4.5), we followed Bishara and Hittner's (2017) recommendations and conducted Spearman's correlations with Fieller, Hartley and Pearsons' (1957) variance when calculating 95 % confidence intervals as these are robust against non-normality.

Table 4.4. Descriptive statistics of actual smartphone use, estimated smartphone use, temporal estimates, and their related errors (n = 23)

Variable	*M*	*SD*	*Min*	*Max*
Median Daily Hours of Use	4.78	3.19	0.64	13.17
Average Daily Pickups	91.73	59.49	40.15	239.77
Average Daily Checks	38.61	34.69	4.69	135.92
Estimated Daily Hours of Use	4.12	1.91	0.42	7.5
Estimated Daily Checks	37.20	24.84	4	100
PC Condition – 53 Seconds Estimate	60.43	22.49	33	120
Phone Condition – 53 Seconds Estimate	61.30	20.72	24	103
Daily Hours Estimation Error	-0.66	2.83	-6.10	5.11
Daily Checks Estimation Error	-1.42	38.50	-85.92	90.77
PC Condition Estimation Error	7.43	22.49	-20	67
Phone Condition Estimation Error	8.3	20.72	-29	50

First, it was of interest to assess whether people could accurately report the daily amount of time they normally spent on their smartphone. To do this, Spearman's correlations were conducted between peoples estimated daily hours of use and median daily hours of use. Findings showed a medium positive correlation between estimated and actual hours of use [$\boxed{r_s}$(21) = .46, p =.03, 95% CI = 0.19, 0.67]. Following, we explored if people could accurately predict their smartphone checking behaviours. To do this estimated daily checks were compared to actual daily checks (uses under 15 seconds). Findings showed a non-significant, small positive correlation between estimated and actual checks [r_s (21) = .25, *p* =.24, 95% *CI* = -0.45, 0.51]. Echoing study one, participants could estimate to some degree how much they time they spent on their smartphone. However, participants found it more difficult to estimate the amount of times they checked their phone on a daily basis.

To understand how people's estimates of use deviated from actual use, two new variables were created. Median daily hours of use were subtracted from estimated daily hours of use to create the variable 'daily hours estimation error'. Likewise, average daily checks were subtracted from estimated daily checks to create the variable 'daily checks estimation error'. These two new variables documented the size and direction of people's estimation errors (see Table 4.4). To summarise, 14 (60.87 %) people underestimated the time they spent on their phone on a daily basis and 9 (39.13%) overestimated. Additionally, 11 (47.83%) people underestimated the amount of times they checked their phone each day and 12 (52.17%) overestimated.

It was then explored whether the size of people's errors was related to their phone usage behaviours. Spearman's correlations showed a large negative correlation between median daily hours of use and daily hours estimation error [r_s (21) = -.76, *p* <.001, 95% *CI* = -0.86, -0.59]. Comparable to study one, this indicated that people who spent a lot of time on their smartphone, tended to underestimate how long they spent on their phone, and people who spent a little time on their smartphone tended to overestimate. In a similar manner, there was also a significant and large negative correlation between average daily checks and daily checks estimation error, [$\boxed{r_s}$(21) = -.67, p <.001, 95% CI = -0.80, -0.47]. Mirroring results from usage time, those who checked their phone a lot, tended to underestimate the amount of times they checked their phone, whereby people who checked their phone a little, tended to overestimate the amount of times they checked their phone (see Fig. 4.8.).

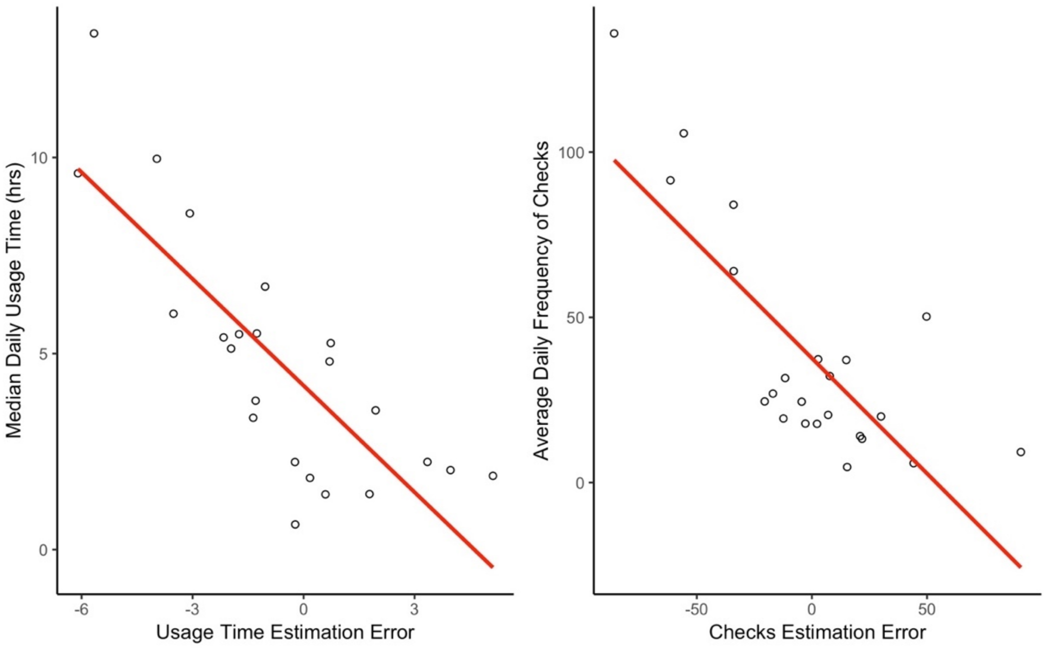

Figure 4.8. Graphs showing the negative correlations between actual smartphone usage and the size of participants estimation errors when measuring daily hours of use and daily checks. Regression line between the two variables is plotted in red.

4.3.2.3. Comparing Errors to Time Estimation Performance

This study was also interested in whether people's smartphone usage estimation errors were related to people's performance on the time estimation task (Wittmann, Leland, Churan, and Paulus; 2007). To begin, a Wilcoxon Signed Rank test was conducted between temporal estimates of 53 seconds when fixating on a computer screen in comparison to when using a smartphone. This was to assess whether perception of time when engaging in smartphone behaviours was different to estimating the duration of none-smartphone tasks. Findings showed no significant difference between the length of estimates between the PC and smartphone condition [$V = 113.5$, $p = .94$, $r = -.01$]. Therefore, the ability to predict time spent on smartphone's is no different to estimating time spent in general tasks. Following, the analysis explored whether the errors people made on this brief time estimation task was related to the errors people made when estimating daily phone use. To create a variable for this analysis, 53 seconds was subtracted from the estimations people gave in the smartphone condition, to calculate the size and direction of estimation errors. Spearman's correlations showed no significant relationships between the errors made when estimating 53 seconds in the smartphone condition and participants daily hours estimation, [$\boxed{r_s}(21) = .34$, $p = 0.11$, 95% $CI = 0.05, 0.58$]. Therefore, performance on the time estimation task did not predict a person's ability to estimate general smartphone usage time.

4.3.2.4. Exploratory Analysis

This chapter aimed to explore the utility of objective logging software when measuring smartphone use, and how this can be effectively implemented in psychological research. Within this aim, it was important to explore how long a person's smartphone behaviours should be monitored for in order to get a representative account of their usage. This would further provide an indication of the degree to which smartphone use is stable and habitual. To achieve this, the data for each person was separated by week. Week one contained a full weekend and four weekdays for all participants (six days in total). Week two contained a full weekend and five weekdays for all participants (seven days in total). The purpose of this splitting was to see how many days' worth of data from week one, was needed to reflect the average usage from week two. Data from all 27 participants were used in this analysis. Three new variables were created for each participant: week two average daily usage time, week two average daily pickups and week two average daily checks.

There is no widely accepted coefficient benchmark for examining convergent validity between two variables. However, it has been proposed that $r < .5$ should be avoided and that coefficients of $r > .7$ are recommended (Carlson & Herdman, 2012). Justification for this benchmark comes from evidence showing that even a small difference between measures can create differing results when correlating with a 3rd variable (Carlson & Herdman, 2012). As the variables assessed here were identical in in their measurement tool across days (objective smartphone logs), higher convergence was expected. Therefore, the benchmark for this analysis was set to $r = .8$ when assessing adequacy.

It was then examined how many days of data from week one was needed to be averaged in order for this average to highly correlate ($\boxed{r_s}$ > .8) with the week two average. Thus, for each smartphone variable, an average for each person was calculated across days two and three of the study. Next, an average for each person was calculated across days two, three and four of the study. Therefore, the amount of days aggregated to create a mean from week one increased in a cumulative fashion and was then compared to the week two average. For each smartphone variable, Spearman's correlations were conducted between all the aggregate scores from week one and the average scores from week two. When examining correlations, using an effect size of $\boxed{r_s}$ > .8 as the cut-off point, the minimum number of days required to infer patterns of smartphone behaviour for an entire week was two days for checks, [$\boxed{r_s}$(25) = .89, *p* <.001 , 95% *CI* = 0.80, 0.94] two days for pickups [$\boxed{r_s}$(25) = .83, *p* <.001 , 95% *CI* = 0.71, 0.91] and five days for usage time [$\boxed{r_s}$(25) = .80, *p* <0.001, 95% *CI* = 0.65, 0.88].

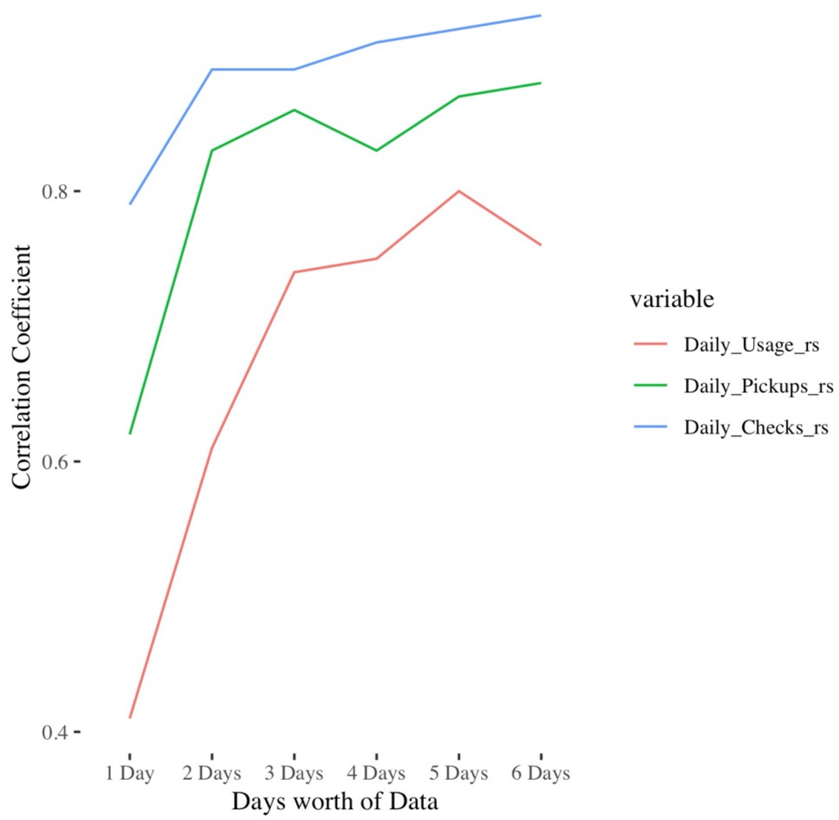

Figure 4.9. Graph showing how many days of data from week one are required to be aggregated in order for this to correlate adequately with average usage from week two. Graph shows correlation coefficients across the three daily smartphone variables; daily usage (in hours), daily pickups and daily checks.

4.3.2. Study two: Summary

Study two is the first study to date that has aimed to understand and define the characteristics of smartphone checking behaviours as well as further assess whether users could accurately recollect these behaviours. The data collected here showed peaks of use occurring at 1 second, 2 seconds, 5 seconds, and 10 seconds intervals, suggesting that habitual actions are likely to be less than 15 seconds in duration. These 'checks' made up 42.50% of all recorded smartphone uses. In the lab it took participants on average 8.42 second, to read a text message, and therefore these peaks are likely to reflect smartphone behaviours such as checking the time, notifications, or messages. When correlating estimated checks with actual daily checks, correlations had small effect sizes. Therefore, in line with the theories which posit that smartphone use is habitual (see chapter 3), and theories of absent-minded smartphone use (Marty-Dugas et al., 2018), participants could not adequately recall how many times they checked their phone per day. This provided support for hypothesis two which posited that participants would find it difficult to recall daily pickups and checks.

Additional findings confirmed several results from study one on a separate sample of Android users, when using logging applications which do not provide feedback to the user. Notably, a medium positive correlation was found between estimated and actual daily hours of smartphone use, which is slightly less than predicted in hypothesis one. When examining the size and direction of errors, for both daily checks and usage time, heavier users underestimated, and light users overestimated their smartphone behaviours. This partially supports hypothesis three, which predicted that the more a person uses their smartphone, the greater their estimation error will be. Theoretical reasons for this are proposed in the discussion section of this chapter, however, there appears a strong linear component when modelling the retrospective estimation errors of technology use, as effect sizes across correlations were large. Therefore, actual smartphone behaviours are a better predictor of estimation errors than performance on the lab-based time estimation task (Wittmann, Leland, Churan, & Paulus, 2007) which showed no significant relationships. However, this null result may have occurred because this task could be considered a prospective estimation task, requiring different attentional and memory processes to retrospective estimations (Grondin, 2001).

Exploratory analysis also found that smartphone usage behaviours were relatively consistent on a day-to-day basis (see Figure 4.7.) When examining daily usage time, five days of data was shown to be representative of a person's overall smartphone use (see Figure 4.9.). However, when examining either smartphone pickups or checks, researchers only need to collect 2 days' worth of data. This provides additional support that smartphone usage is habitual, especially for checks and pickups. Therefore, checking behaviours may be driven by automatic processes, highlighting further that it would be difficult to self-report these behaviours.

4.4. Discussion

The purpose of this chapter was to carry out a methodological exploration which evaluated the efficacy and validity of different tools which were created to measure smartphone use. Specifically, three different measures were compared: subjective estimates of use, psychometric scales and applications which directly log use. Despite the popularity of subjective estimates and psychometric usage scales (Boase & Ling, 2013; Ellis, 2019) results across both study one and study two suggest that these provide sub-optimal information about a person's usage behaviours. Notably, when compared to direct logs, neither subjective estimates nor psychometric scales correlated with high enough effect sizes (r_s > .7) to claim they were operationalising smartphone use as well as objective logs.

Psychometric scales have traditionally been created to capture a feeling, behaviour or an action that cannot be accessed directly, or cannot be described by a single item alone (i.e. the construct 'love' is considered multifaceted) (Boateng, Neilands, Frongillo, Melgar-Quiñonez, & Young, 2018). Yet in this chapter, it has been shown that scales which claim to measure 'problematic usage' or more general use cannot be used as a proxy for behavioural measurements (Elhai et al., 2017). As this was found across many popular scales that are used in the field, this shows that results are not spurious due to characteristics of a particular scale and illustrate that this issue is likely widespread. Therefore, it is not appropriate to use a problematic or general usage scale instead of measuring actual use when making conclusions regarding the time people spend on their devices. Further when assessing 'tolerance' or 'overuse' by examining if actual time spent on the device relates to problematic usage scales, the relationship is smaller than expected, given this a core component of problematic use as a construct (Billieux, Maurage, et al, 2015; Elhai et al., 2017; Kim, 2017). Therefore, researchers should shift away from the repetitive development of psychometric scales which dominates much of the literature when aiming to measure use (Ellis, 2019), and instead focus on fine-tuning measures which have greater validity.

To further this point, when utilising psychometric scales, it is thought that through aggregating an accumulation of questions which measure the same construct, this avoids item-specific measurement errors, leading to more accurate research findings (Boateng et al., 2018). Contrary to that assumption, it was found in study one and two that a single estimate of usage outperformed all scales when compared to objective logs. Being easier to create and administer, this would appear to be the measurement of choice for self-reports. Moreover, by asking a single estimate, there would be less variability in measurement across studies.

However, even single estimates fail to explain more than a third of the variance in actual usage behaviours. In study one and two when examining the relationships between actual and estimated daily screen time/hours of use, correlation coefficients ranged from .46 to 56. This is in-line with previous work which aimed to validate subjective estimates with objective technology logs, as the average correlation coefficient across previous studies was r = 0.53 with a range of .46 to .60 (Boase & Ling, 2013; Parslow, Hepworth & McKinney 2003; Kobayashi & Boase, 2012; Lee et al. 2017). In contrast, in study one and two, effect sizes dropped below this when examining daily pickups ($\boxed{r_s}$ = .40) and checks ($\boxed{r_s}$ = .25). Notably, in study two usage sessions were short as 55.86% of uses were under 30 seconds and 42.50% were under 15 seconds. This supports the view that pervasive checking behaviours may operate more habitually, with less conscious awareness, and as a result, are more difficult to recollect than usage durations in general (Oulasvirta et al., 2012).

When additionally examining the estimation errors people made across studies one and two, the magnitude of these errors negatively correlated with a person's actual smartphone use with large effect sizes. Specifically, findings showed that people who spent a lot of time on their smartphone tended to underestimate how long they spent on their phone and people who spent a little time on their phone tended to overestimate. Therefore, whilst increased smartphone use did increase estimation errors in line with hypothesis three, those who used their phone very little also made estimation errors in the opposite direction. These findings could be explained by the memory marker model of time perception, which describes how rich activities with lots of context changes, such as engaging with smartphones would be reported as longer than reality after a delay (Ahn et al., 2009). This is because engaging events evoke a larger number of 'memory markers' to be encoding in memory, which on reflection, makes that duration seem longer (Ahn et al., 2009). It is possible that this cognitive process is occurring for the over-estimators here, who used their phone a little.

However, the memory marker model of time perception also explains the estimation errors in the reverse direction. It has been shown in a retrospective estimation task, that repetitive and routine visual stimuli are perceived as lasting shorter after a delay, when compared to richer and engaging visual stimuli (Ahn et al., 2009). This is because, as an event becomes more habitual, less encoding occurs in memory, resulting in durations being perceived as shorter after a delay (Ahn et al., 2009). Consequently, as smartphone use increases and becomes more repetitive, a person's duration of use would be perceived as shorter. Interestingly, as the negative correlation crosses zero, it is possible to see the turning point from underestimating to overestimating (see Fig. 4.1. and 4.8). One could speculate that both of the cognitive mechanisms described above would also switch in dominance at this zero-crossing.

Both Figure 4.1. and 4.8. suggest that those who use their phone for ~4 hours or more are using their smartphone in a predominately automatic fashion.

Collectively, these findings have wide ranging consequences for the vast number of studies that rely on these self-reported measures as a proxy measure of behaviour (Boase & Ling 2013). For example, through the use of self-reports, large claims have been made pertaining to the impact that technology has on public health, most commonly with mental health (Thomée, 2018; Twenge, 2019). However, as these studies lack criterion validity, their results may have incorrect conclusions which could mislead other researchers, casual readers, and policy makers (Ellis, 2019). Due to its pertinence, exploring whether there are errors in measurement when making conclusions regarding smartphone use and health is explored further in chapter six.

Results from chapter four also provide direction for future research which aims to capture smartphone behaviours. Notably, due to the consistency in smartphone usage patterns, five days of data is adequate enough to provide a representative account of a person’s smartphone usage. This drops to just two days if examining pickups or checking behaviours. This has important implications for data collection in future studies; ethically only the data required to answer the research question should be collected. This is particularly pertinent to rich smartphone logs of human behaviour, to further protect participant privacy.

Additionally, whilst computer scientists have been documenting objective usage logs for several years, it is advocated that psychologists should also adopt this direct behavioural measurement, to ensure research has accurate conclusions (Piwek et al., 2016). This chapter therefore provides two examples of how smartphone use can be directly measured, each with their own benefits and drawbacks. ‘Apple Screen Time’ (Apple, 2018) is arguably the most accessible way for those without programming experience to access objective logs of smartphone use. This feature is already built into any iPhone which has iOS 12 or later installed, and automatically logs usage without any participant effort. This data is easily extractable for participants to enter into online surveys, as the tool displays daily and hourly smartphone use for the past seven days. Consequently, usage data can be collected on a large, representative samples in one testing session, as usage statistics can be viewed retrospectively.

However, as participants are still required to extract data from ‘Apple Screen Time’, and re-enter the numbers into online surveys, there is the possibility of human error as this procedure gives participants the opportunity to change their responses due to social desirability biases. Further, it is possible that participants may have looked at their own smartphone use before providing an estimate, as ‘Apple Screen Time’ provides usage feedback. However, as findings from study one mirror conclusions from study two whereby the logging application automatically sent data to the researcher, and did not provide participants with feedback, it appears these limitations did not largely affect the quality of this data. This also shows that any differences between iPhone and Android users (see chapter three) did not influence the way people estimated their smartphone usage.

When collecting usage data from Android users, recent frameworks allow psychologists to develop applications in less than 30 minutes (Aharony et al., 2011). Android applications do not have the same restrictions imposed by Apple iOS and can therefore, log usage to a higher resolution. Additionally, they can place smartphone logs into a data file without participant involvement. However, this approach requires scripts to automatically process the data, as second-by-second logs produces rich and large data files (Andrews, et al., 2015). Data is also not collected instantly, as the application in study two prospectively logged smartphone usage across the study duration and data was sent to the researcher each evening. This longitudinal method is therefore vulnerable to participant attrition. There was a final limitation, which is a product of the Android operating system; if a smartphone loses battery or is switched off, the system will not log a 'screen off' event and is therefore not captured by the application. This is controlled for by using medians in study two so that results were not influenced by extreme values which occurred if the smartphone was off for a long period overnight. To summarise, by studying usage across both iPhone and Android methodologies, it is possible to control for limitations of both approaches.

In contrast, there are several benefits to the tools used in study two as high-resolution data collected by the Android application allows for data to be split into infinitely divisible time intervals. Examining how much people actually use their smartphone in this detail can be useful for a variety of applications. For example, all except one participant in study two used their phone as an alarm clock, and most reported that they always use their phone last thing before sleeping. These usage patterns can therefore provide a non-invasive indication of sleep length (see Fig. 4.4.), which has the potential to augment sleep diary data (Natale, Plazzi, & Martoni, 2009). It was also possible to define what constitutes as a smartphone check, and how often a person conducts this behaviour by examining short uses that lasted under 15 seconds of duration. Consequently, it is possible to learn a lot about an individual from a very simple digital trace; binary smartphone activity logs.

To conclude, across the majority of existing research, there was no single commonly accepted way to measure smartphone use (Boase & Ling 2013). Thus, establishing a 'gold standard' measure of usage behaviours, that is accepted across studies can increase the credibility and reliability of future research. Findings from chapter four showed that self-reports may have inaccuracies that could lead to incorrect conclusions when studying smartphone use. Notably, the errors people make when estimating daily smartphone usage did not appear to be due to random noise, but instead likely to be caused by human perceptual and cognitive capabilities. This lack of validation between self-reports and objective measures feeds into a growing consensus in Psychology that the discipline faces issues with measurement, in addition to the current replication crisis (Flake & Fried, 2019). Therefore, if usage is the topic/variable of interest when conducting research, this should be measured directly now that tools and frameworks are becoming increasingly accessible. Even simple on/off data can provide rich information about a person's routine, usage habits and patterns which cannot be captured through psychometric tests or estimates. Consequently, objective logging applications are likely to provide the most accurate and detailed account of our smartphone usage in future research, and furthermore be the most informative when understanding a user's individual differences from digital traces of smartphone behaviour.

Chapter 5

Predicting Individual Differences from Smartphone Use

5.1. Introduction

Gathering data about the attributes of a person or group typically relies on self-report personality questionnaires (Barford, Zhao, & Smillie, 2015). However, new approaches in behavioural science describe how analysing digital traces of behaviour from mobile devices and online activity can be used to produce personality assessments (Hinds & Joinson, 2019). Data can be collected remotely 'in situ' while the respondent engages with their normal, everyday activities. This approach requires little to no engagement from the person being assessed and mitigates issues such as response bias, question confusion and low introspective ability (Rosenman, Tennekoon, & Hill, 2011). Meta-data such as the smartphone operating system a person uses has previously been shown to predict personality traits and demographics in chapter three. When additionally integrating the methods explored in chapter four, this chapter can explore the possibility of profiling a user's characteristics using none-intrusive smartphone applications which record a person's day to day smartphone activities.

Screen time and application use have been shown to be related to personality and demographics when using self-reports to measure smartphone use. In a panel of 9582 people across Korean households, each standard deviation increase in the personality traits openness, extraversion and conscientiousness was associated with an increased probability of using smartphones (Kim, Briley, & Ocepek, 2015). Women in this study self-reported that they used relational applications in greater amounts than men, and as age increased, so did the likelihood of using e-commerce applications. It has also been self-reported that 60% of men use instant messaging applications consistently in comparison to 73.53% of women (Anshari et al., 2016). Others describe how extraversion is related to greater use of social applications (Tan, Hsiao, Tseng, & Chan, 2018). Finally, pathological use of smartphones has also been associated with differing personality traits. For example, “cell phone” addiction is shown to be positively associated with emotional instability and materialism, and negatively associated with introversion (Roberts, Pullig, & Manolis, 2015).

Whilst the above is based on self-reports, chapter four outlined the methodological considerations for technology-based research. Notably, objective logs of technology use provide a more valid way of collecting data on a person’s technology related behaviours than temporal estimates or capturing use via psychometric scales. In addition, through the use of objective data, it is now possible to find new technology specific user characteristics. For example, previous research analysed application usage logs to define distinct types of smartphone users such as ‘checkers’ who revisit applications frequently within an hour, and ‘waiters’ who re-use applications after a longer period of time (Jones, et al. 2015). Through using these methods, it is also possible that groups of individuals can be identified from smartphone usage patterns, as Zhao et al. (2016) found that when clustering application usage from 106,762 people, that hundreds (382) of distinct types of users emerged.

Furthermore, as objective logs contain rich ‘within-subject’ data by collecting second by second usage, investigations concerning how smartphone use can reveal user characteristics, can also incorporate ideographic approaches. Defined as *“the unique understanding of that individual’s personality”* with the goal of developing *“an in-depth understanding of the individual”* (Maltby, Day, & Macaskill, 2010, p. 8) the rich data gathered by smartphone usage applications can be used for this purpose. For example, when using smartphone logs, a person's unique sleep patterns can be inferred from a large period of inactivity over-night and waking can be identified from smartphone alarms in the morning (see chapter 4). Therefore, the aim of this chapter is to carry forward these methodological advancements to ascertain if smartphone use can highlight a person's individual differences when using both nomothetic personality assessments (e.g., the HEXACO) and ideographic assessments (e.g., consistent patterns in 'within-subject' usage traces).

Traditionally, nomothetic approaches summarise individuals through their locus on 5-6 core traits, and examine similarities between groups of individuals (Maltby, Day, & Macaskill, 2010). When administering personality assessments, an individual's scores on each trait have been shown to predict behaviour (Fleeson & Jayawickreme, 2015). When applied to objective smartphone use, Stachl et al. (2017) found that extraversion, conscientiousness, and agreeableness were better predictors of smartphone application use than basic demographic categories. Data mining approaches have also found that extraversion, agreeableness, conscientiousness and emotional stability correlate with SMS, application usage and call logs (Chittaranjan, Blom, & Gatica-Perez, 2013). Further research has found that extraversion can be predicted from smartphone data on a large sample of 730 students (Mønsted, Mollgaard, & Mathiesen, 2018). Lastly, classification models have used smartphone data to predict user personality with up to 75.9% accuracy (Chittaranjan, Jan, & Gatica-Perez, 2011). Therefore, it is possible that personality traits can be predicted from objective smartphone usage logs.

All the studies above adopted a 'Big 5' model of personality, whereby a five-factor solution, consisting of five personality traits is accepted (Maltby, Day, & Macaskill, 2010). However, recent factor analysis research across several languages has suggested that six (rather than five) core personality characteristics exist and these are honesty-humility, emotionality, extraversion, agreeableness, conscientiousness and openness-to-experience (HEXACO) (Ashton, Lee, & de Vries, 2014) (for a review of HEXACO v's traditional 'Big 5' approaches, see chapter three). Notably, honesty-humility was shown to be the strongest personality predictor of smartphone ownership in chapter three. This suggests new insights can be found when relating smartphone use to personality traits through the use of the HEXACO model, beyond what is found when using the 'Big 5'. Therefore, it is explored in this chapter whether objective smartphone usage behaviours correlate with personality when utilising the HEXACO framework (Ashton, Lee, & de Vries, 2014).

A new variable, 'smartphone checks', defined in chapter four as "any usage under 15 seconds", has also not been explored in terms of its relationships with personality. Frequency of checks is a different smartphone variable to frequency of pickups (total number of uses) as checks consist of usage sessions which are short in duration. Specifically, in chapter four, it was shown that smartphone checks were highly consistent within the same user across several days. Therefore, patterns of checking behaviours could be unique to the individual and provide information about their characteristics. This provided support for the Technology Integration Model (TIM), outlined in chapter 2 which posits that over time the use of a technology becomes increasingly habitual in response to contextual cues. Therefore, it is explored in this chapter whether smartphone checks are related to HEXACO personality traits alongside whether they can be explored in a more ideographic way.

Theories such as the Cognitive-Affective Processing System (CAPS) also suggest people have behavioural signatures/responses which are stable in situations which are perceived psychologically as being the same (Mischel, 2004)). This ‘interactionist’ account may be expressed using *if...then* statements. If in Situation X, then he/she does behaviour A, but if in Situation Y, then he/she does behaviour B (Shoda, Mischel, & Wright, 1994). Therefore, it may also be possible that people exhibit the same behaviours when using the same smartphone application. This theory takes into account how people behave differently across different situations whilst describing how a person’s behavioural responses to specific situations are consistent. Unlike typical approaches to personality/behaviour (Maltby, Day, & Macaskill, 2010), both the TIM and the CAPS model encourage the assessment of intraindividual stability over time, and a rich ideographic assessment of a person’s unique usage behaviours.

Support for CAPS can be found in existing literature which explores smartphone use patterns. Aledavood et al., (2015) analysed the call patterns of 24 individuals over an 18-month period and found that the frequency of calls at each hour of the day was distinct and persistent within an individual. Consistent temporal cycles in technology use are also found in text message records, email records and smartphone screen time logs (Aledavood, Lehmann, & Saramäki, 2018, 2015). Therefore, it appears that the variance in daily technology use behaviours may be distinct between people, but consistent within the same person.

Here I present a research project which involves using two applications, developed within the PsychSensor lab group, that document real-time smartphone usage on Android devices. The applications log screen time and application use every second to accurately record everyday smartphone use behaviours. Chapter three found that personality, gender, and other characteristics could be predicted from a very simple digital trace; a user's smartphone operating system. Likewise, it is anticipated that a person's screen time and application use can be predicted from objective smartphone use. Extended self theory (Belk, 1988, 2013) and the Technology Integration Model described in chapter two would posit that the more power and control a person has over their technology use, the greater it becomes an extension of themselves. Following this line of thought, if variables such as screen time and application use allow for greater variation between participants than smartphone operating system choice, then it is possible that user traits become more predictable.

Hypothesis one: Smartphone usage behaviours will significantly relate to scores on each of the HEXACO personality factors.

It is also likely that demographics can be predicted from smartphone behaviours. In chapter two, gender and age were shown to predict smartphone ownership. Specifically, increases in age were shown to reduce the likelihood of owning an iPhone and women were twice as likely to own an iPhone device than an Android. When reviewing existing literature which measured smartphone use objectively, a recent communication market report found that length of application sessions increased with age when using Chrome, Google play store, Twitter, WhatsApp, BBC News, and eBay applications (OFCOM, 2018). Gender differences were also explored; men spent longer on the Google play store and BBC News applications, whereas women spent longer on Facebook, Chrome, Instagram, YouTube, WhatsApp, Snapchat, and Amazon shopping (OFCOM, 2018). Therefore, it is expected that objective smartphone use can predict a user's demographics.

Hypothesis two: There will be significant differences in smartphone usage variables between men and women.

Hypothesis three: Increases in age will predict changes in smartphone usage behaviours.

To expand on previous work, we explore here if a user's checking and application usage behaviours is both distinct and has 'within person consistency' across days of the study. Interindividual stability of application use is modelled through examining daily behaviour profiles of application use, mirroring traditional behavioural consistency approaches (Shoda, Mischel, & Wright, 1994). Previous day-to-day application usage has been found to be the most consistent "sensed social behaviour" when examining intraclass correlations of conversation calling, texting and application use (Harari et al., 2019). Alongside checking behaviours, it is therefore explored if daily application usage patterns can act as a 'digital fingerprint' highlighting a person's unique characteristics.

Hypothesis four: Users can be identified from their distinct daily checking and application use behaviours.

5.2. Study: Predicting Individual Differences from Smartphone Use

5.2.1. Method

5.2.1.1. Preregistration

The data collection procedures for this study were pre-registered on the open science framework (Shaw, Ellis, Geyer, Ziegler, & Davidson, 2018; https://osf.io/5g9v6). Due to the wide range of individual differences measured, the data is explored across two chapters. Therefore, chapter five and the first study of chapter six share a common dataset. For brevity, the focus of this chapter is to describe how personality and demographics can be predicted from smartphone use. Therefore, only the variables related to this aim are described here. For further information on all the variables collected see (Shaw et al., 2018; https://osf.io/a4p78/). Finally, see chapter six for a description of variables which describe relationships between general smartphone use and health.

5.2.1.2. Participants

80 participants were recruited for the study. However, due to technical issues, nearly half the participants were removed due to incomplete log data. The final sample consisted of data from 46 participants. A priori power calculation determined that a total sample size of 44 was required to investigate two-tailed medium-to-large effect

sizes ($r > .4$) with a power of .8 when $\alpha = .05$. This is similar to other research which collected high frequency smartphone data when correlating personality scores to objective phone usage ($n = 49$) (Montag et al., 2014). Gender had a ratio of 6:17 as 12 (26.08%) out of the 46 were men, and 34 (73.91%) were women. Age was positively skewed as the sample was predominately younger adults [$M = 23.54$, $SD = 8.25$]. All participants were Android smartphone users, whereby 25 (54.34%) owned a Samsung Model, six (13.04%) owned a Sony device and the rest owned other brands such as Huawei, Google, Nokia, and Motorola phones.

The study was advertised around the University campus using posters, leaflets, subject pool systems and social media channels, during term time and during public engagement events. Therefore, the sample consisted of those who emailed the researcher in response to these advertisements. Participants were told they would receive a graph of their phone use and a printout of their health analysis as incentives to take part. Those recruited through subject pool systems were additionally given course credit in compensation for their time.

5.2.1.3. Measures

Personality

The 60-item HEXACO was used to analyse a user's personality across six domain level traits; honesty-humility, emotionality, extraversion, agreeableness, conscientiousness, and openness-to-experience (see chapter 3 for a detailed description of each trait) (Ashton & Lee, 2009). Only single factors were examined rather than facet-level personality scores as these have previously shown to have higher predictive performance when predicting personality from phone logs (Stachl et al., 2017). For each trait, ten questions were answered concerning how much a participant agreed or disagreed with a statement about themselves. Answers were recorded on a five-point Likert-style scale, whereby five = *'strongly agree'* and one = *'strongly disagree'*. Reliability analysis showed that all trait scales had good internal reliability, apart from honestly-humility ($\alpha = 0.65$) and openness-to-experience ($\alpha = .78$) which fell below the .8 threshold.

Demographic Information

Self-report questions were used to measure gender, date of birth, marital status, highest qualification, and job sector. Gender was measured through the selection of six options on a multiple-choice question: *'Female'*, *'Male'*, *'Transgender'*, *'Gender Variant/Non-Conforming*', '*Not Listed (please specify)*', and '*Prefer Not to Say'*. Participants selected one of five options for marital status: *'Single'*, *'Married/Civil Partnership'*, '*Widowed*', *'Divorced'*, and *'Separated'*. Job sectors were taken from the UK Prospects websites and included 24 categories ranging from accounting to transport & logistics (Prospects, 2019). Highest qualification was measured through a multiple-choice question containing each of the eight UK levels with examples of what qualifications constitute to each level (UK-Government, 2019).

The MacArthur Ladder of Subjective Social Status was used to measure a person's perceived social economic status in society (Adler, Epel, Castellazzo, & Ickovics, 2000). In this scale, participants viewed a picture of a ten-step ladder. The instructions were: *"There are 10 steps on this ladder. At the top of the ladder are the people who are the best off, those who have the most money, most education, and best jobs. At the bottom are the people who are the worst off, those who have the least money, least education, and worst jobs or no job. On the multiple-choice options below, please select a step which best represents where you stand on this ladder"*. Like chapter three, this was used instead of collecting details about pay or household income.

Smartphone Measures

Objective smartphone data was collected across two applications developed specifically for the study, Activity Logger and App Usage Logger (Geyer, 2018a; Geyer, 2018b; Geyer et al. 2020). These ran on Android devices and collected data to the resolution of one second. Activity logger measured three signals which were monitored by broadcast receivers: the phone being turned on, the screen becoming activated, and the screen turning off. Background operations (services) would be alerted by these signals indicating whether the screen was turning off or on. These background operations then took this information, retrieved the current time stamp, and stored this in internal memory. This data could then be exported through the application as a .txt file containing a list of records whereby a UNIX time stamp was paired with an event stating whether the screen was becoming "on" or "off".

In principle, app usage logger operated in the same way but, had an additional response when the screen was turned on and off. When the screen was turned on a function would repeat every 200 milliseconds. The function would query a database (UsageStats, 2019) generated by Android and independent of the application. This database stored a record of what applications were being used for the past two years on an Android device. The query would only question what application was running in the foreground for the past second. If this was the first time the function had ran since the screen was turned on or identified a different application from the previous time the function ran, then the name of the application would be documented in the internal memory along with a UNIX timestamp. However, repetitively running this function would be require extensive amounts of processing power and therefore to save battery the application would stop calling this function while the phone screen was off. App usage logger would also document meta-data including installed applications, the deletion and installation of applications across the week, and smartphone unlocking. Source code for both applications are available to download (Shaw et al., 2018; https://osf.io/a4p78/).

5.2.1.4. Procedure

The study lasted a duration of nine days. Prior to the study, participants were sent an infographic outlining the itinerary and data that would be collected across the nine days (see Fig. 5.1). Participants would also confirm via email the ownership of an Android smartphone. If participants were interested in taking part in the study after viewing the infographic, they were invited to the lab for day one. This first lab session provided participants with detailed study information, including example data, followed by a consent form and an online questionnaire. The online questionnaire was hosted on Qualtrics and included demographic questions, including date of birth, gender, marital status, highest qualification, job sector and social economic status.

Afterwards, they completed the 60 item HEXACO. Finally, they completed several health variables measuring happiness, personal wellbeing, and loneliness.

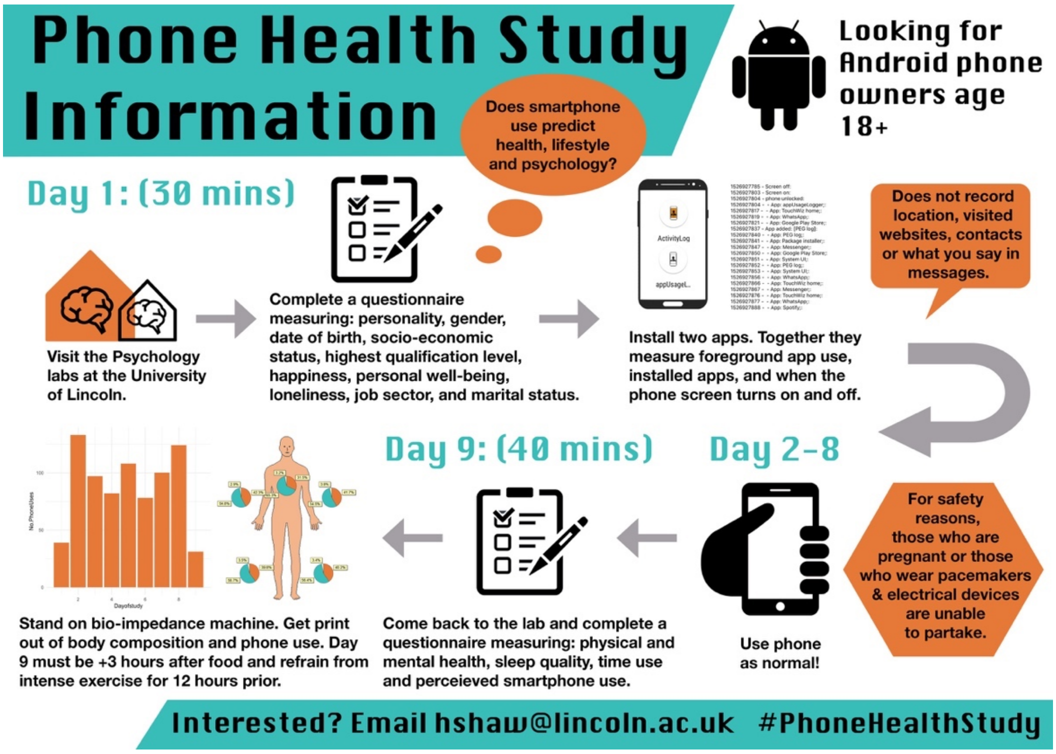

Figure 5.1. *Study infographic used to advertise the project. Describes the itinerary of the study and what measures are collected across which days.*

Once completed, participants were guided through the installation of activity logger (Geyer, 2018a) and app usage logger (Geyer, 2018b), and the researchers documented the smartphone brand and operating system. All screen savers were set to turn off after 30 seconds, and the applications were 'white listed' in the smartphones' battery settings, ensuring that the phone would not 'force quit' some of the applications to conserve battery. Participants were then asked to keep their phone switched on for the duration of the study, and to keep the applications running in the background. Whilst the applications should re-start independently, as a precaution, if a participant's phone was switched off or had a fully depleted battery during the week, participants were instructed to re-open the applications once the phone had restarted. Participants were then provided with information detailing how to prepare for the body composition assessment on day nine. To control for factors influencing body composition results, participants were asked to refrain from intense exercise and alcohol consumption up to 12 hours prior to the assessment, to maintain hydration, to book a time in the afternoon that was three hours after lunch, and to go to the toilet before the session.

Participants were then asked to use their phone as normal, and to carry on with their everyday activities across days two to eight of the study. This ensured that seven full days of smartphone data was collected for each participant. On day nine, they returned to the lab and upon arrival, emailed the data from the application to the researcher. Next, participants completed a questionnaire containing stress, anxiety, depression, and smartphone addiction scales (see chapter six). They further answered questions on ocular symptoms, musculoskeletal symptoms, and sleep quality. They were then asked to provide a daily average estimate of how much they picked up their phone, and the amount of time they spent on their phone across days two-eight.

Height was measured for the bioimpedance assessment, an objective health measure described in chapter six which documents a person's body composition including muscle mass and body fat percentage. Participants were instructed to remove any jewellery, items in pockets and metal accessories, and were then asked to stand bare foot on the Tanita MC-780MA body composition monitor while holding the hand electrodes by either side of their body, without touching their legs. A 0.5kg clothing allowance was inputted into the Tanita software if participants were wearing light clothing (sports/gym gear), and a 1kg clothing allowance was inputted for heavy clothing (jumpers, jeans). Upon completion, participants were given a printout of their body composition, a graph of their application use, and of their screen time across the week. Finally, participants were debriefed and thanked for their time.

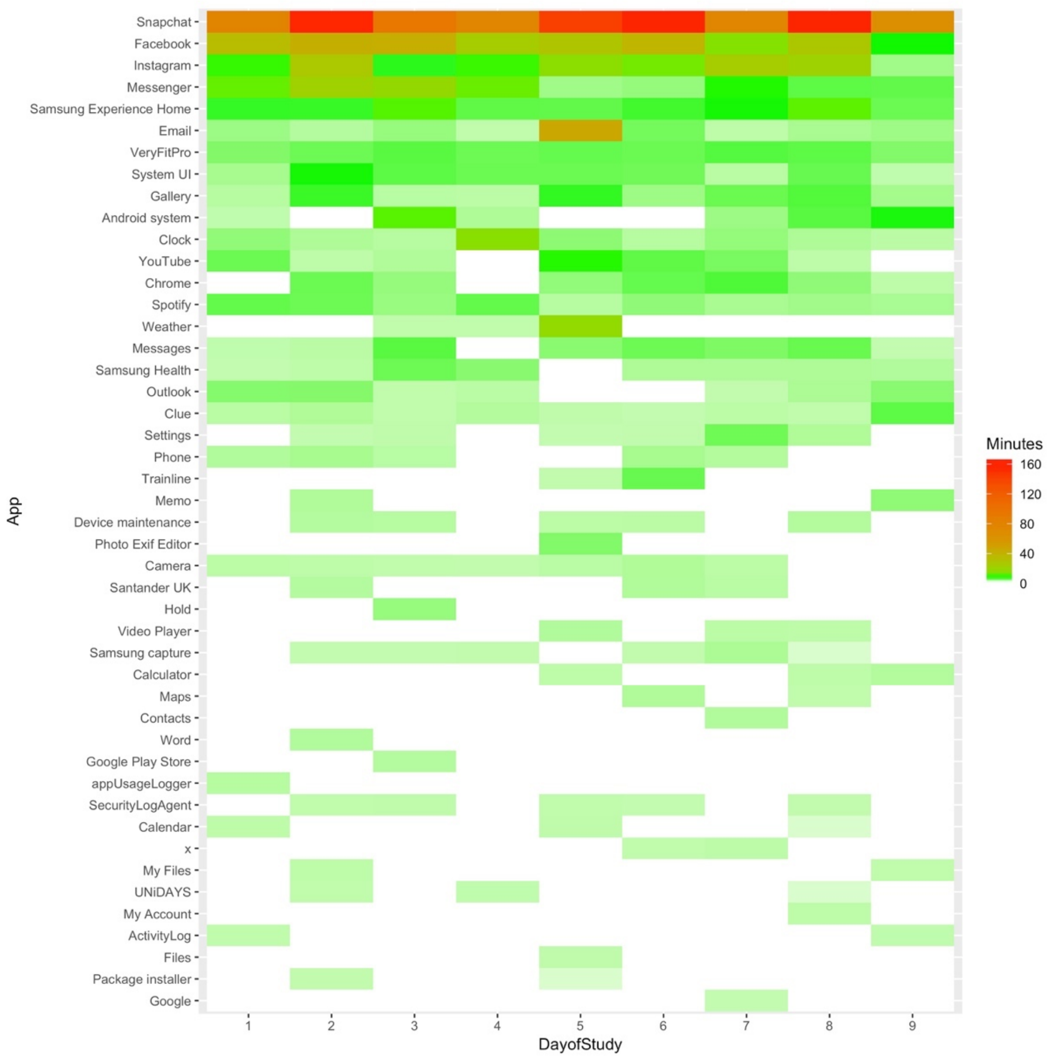

Figure 5.2. Example heatmap provided to participants containing data from app usage logger. Along the x axis is the day of the study, and along the y axis is the application used. Colours represent how many minutes per day an application was used for. A pale green shade indicates lesser use, and a bold red shade indicates increased use.

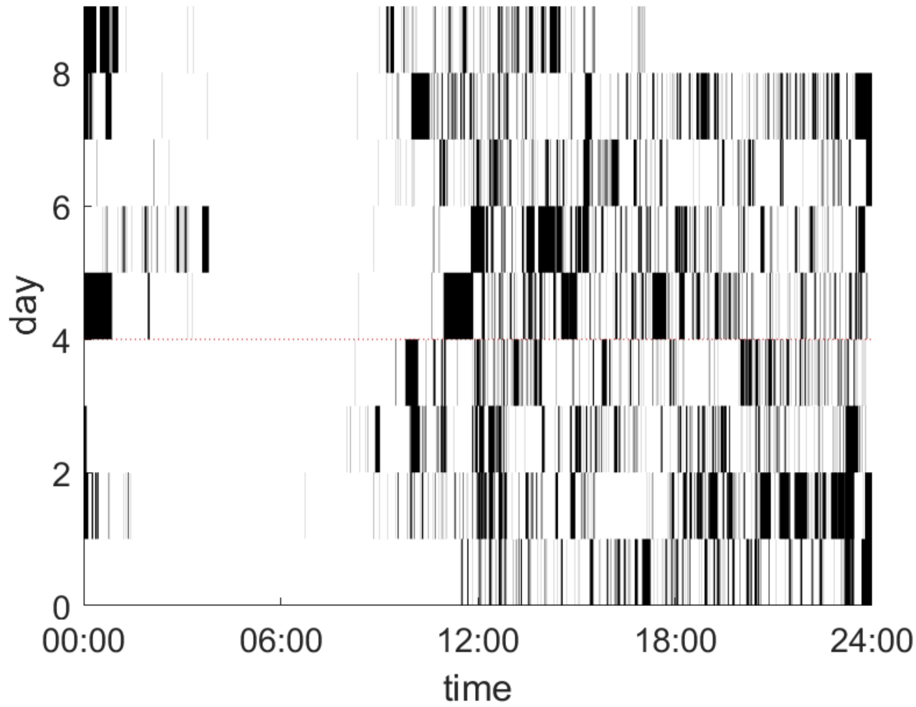

Figure 5.3. Example smartphone barcode provided to participants containing data from activity logger. These were identical to those presented in chapter four. Black bars indicate when the phone was in use. Each row represents a unique day, and red dots indicate the beginning of a weekend.

5.2.1.5. Ethics

All procedures received ethical clearance by the University of Lincoln and complied with BPS ethical guidelines (British Psychological Society, 2018). No deception took place during this study as participants were shown example data which allowed them to understand exactly what information would be collected from their device. The study also underwent a data protection plan. Participants had full control of their data across the duration of the study as phone logs were stored solely on their devices. Therefore, at the end of the study, participants could choose whether to share their data with the researcher. Equally, they could access their own phone data by emailing the .txt file to themselves throughout the study. Deleting either application would also remove its data from the device and therefore, was a method of withdrawing from the study, alongside emailing the researcher and ethics committee. Participants were assigned a ID number, which was paired with their phone, survey and bioimpedance data to maintain anonymity.

5.2.2. Results

The data collected for this project is available to download on the open science framework (Shaw et al., 2018; see https://osf.io/a4p78/).

5.2.2.1. Analysis Plan

The following analysis is separated into six sections. To begin, an outline of how each scale is coded and formulated into scores is described. Thereafter, a description of how the smartphone data was processed, to generate variables which could be assessed in the analysis, is presented. The third section details the descriptive statistics derived from this smartphone data, including distributions of use frequencies and the most used applications. Then, how individual differences related to smartphone use was explored, including whether there were any significant relationships between a user's personality traits and smartphone variables. Relationships with age were also examined alongside mean differences of smartphone use between men and women. Finally, the fifth and six section detail the analysis that was conducted to ascertain if users can be uniquely identified from their smartphone data, due to a consistency in both checking and application use behaviours across days of the study.

5.2.2.2. Scoring

For every personality trait in the HEXACO model, the responses to its ten questions were summed and then divided by ten to create an average. This generated six trait scores, one for honesty-humility, emotionality, extraversion, agreeableness, conscientiousness, and openness-to-experience.

5.2.2.3. Smartphone Variables

Smartphone data from days one and nine were removed from the analysis to ensure only days which contained a full 24 hours of smartphone data were analysed. This left seven complete days of data per person. Screen time data from activity logger was then processed by extracting 'screen on' events and their durations for each 24-hour time period (midnight to midnight). All durations for that day were summed to create a daily amount of screen time which was then converted from seconds into hours. The median daily hours-of-use was then calculated across the seven days to create an aggregate measure per person. Medians were used as a control to remove the influence of extreme values which on rare occasions were present if the smartphone lost battery, and the application could not log a 'screen off' event.

In addition, daily pickups were calculated by analysing the frequency of 'screen on' events for each day. As defined by chapter three, daily checks were also calculated by examining the frequency of 'screen on' events per day which were less than 15 seconds in duration. Following the average frequency of pickups and checks were also calculated across the seven days. When analysing data from App Usage Logger, statistics were generated for individual applications in the exact same way as screen use statistics, calculating their hours of use, pickups and checks across each day. Additional meta data was also collected. See table 5.1. for a summary all smartphone variables.

Table 5.1. A list of phone variables derived from activity log and app usage logger data.

Smartphone Variable	Extraction Procedure
Average Daily Phone Unlocks	Count the number of unlock events across each 24-hour period and average across the seven days.
Average Daily App Loads	Every time the foreground app changes, via application loads or app switching, a log is documented. Count the frequency of individual app loads across each 24-hour period and average across the seven days.
Average Daily Unique Apps	Across each 24-hour period, list the apps which were used. Count these to create a sum and average across the seven days.
Number of Installed Apps	On day one, app usage logger documents a list of installed apps. Count the number of apps.
Median Daily Screen Time (Hrs)	Extract 'Screen on' events and their durations for each 24-hour time period. All durations for that day were summed to create a daily amount of screen time and was then converted from seconds into hours. The median daily hours-of-use was calculated across the seven days.
Average Daily Pickups	Analyse the frequency of "Screen on" events for each 24-hour time period and average across the seven days.
Average Daily Checks	Analyse the frequency of "Screen on" events that were less than 15 seconds in duration for each 24-hour time period and average across the seven days.
Median Daily Hours of Inactivity	Extract 'Screen off' events and their durations for each 24-hour time period. Sum to create a daily amount of inactivity and then convert from seconds into hours. The median daily hours of inactivity were calculated across the seven days.
Average Daily Screen Offs	Analyse the frequency of "Screen off" events for each 24-hour time period and average across the seven days.
Average Screen on Duration (sec)	Across the seven days, on average, how long was each "Screen off" event in seconds.
Average Inactivity Duration (sec)	Across the seven days, on average, how long was each "Screen off" event in seconds.
Average App Daily Checks	Same as 'Average Daily Checks' with data exclusively from specified app.
Average App Daily Pickups	Same as 'Average Daily Pickups' with data exclusively from specified app.
Average App Daily Screen Time (Hrs)	Same as 'Median Daily Screen Time (Hrs)' however a weekly average was calculated rather than medians, with data exclusively from specified app.

Table 5.2. Means and standard deviations of the study variables (n = 46)

	M	*SD*		*M*	*SD*
Person Variables			Smartphone Variables		
Age	23.54	8.25	Average Daily Phone Unlocks	77.54	40.53
Highest Qualification Level	4.02	1.57	Average Daily App Loads	352.67	197.24
Social Economic Status	5.17	1.27	Average Daily Unique Apps	26.33	6.54
Honesty-Humility	3.52	0.53	No. Installed Apps	79.54	26.75
Emotionality	3.54	0.66	Median Daily Screen Time (Hrs)	3.74	1.60
Extraversion	3.10	0.73	Average Daily Pickups	133.18	63.52
Agreeableness	3.25	0.69	Average Daily Checks	58.06	38.75
Conscientiousness	3.70	0.60	Median Daily Inactivity (Hrs)	19.84	1.86
Openness-to-Experience	3.48	0.69	Average Daily Screen Offs	133.18	63.51
			Average Screen On Duration (Secs)	28.11	15.83
			Average inactivity Duration (Secs)	211.38	278.96

5.2.2.4. Smartphone Descriptive Statistics

On average participants used their phone for 3.74 hours and day [*SD* = 1.60] and picked up their phone 133.18 times a day [*SD* = 63.52]. When collating all 46 participants' data together, smartphone use was highly skewed as 54.44% of uses were under 30 seconds in duration and 43.54% of uses were under 15 seconds in duration. When plotting the frequency of uses which lasted a specified duration, distinct peaks of use occurred at two seconds, six seconds, and eleven seconds (see Fig. 5.4.). These may represent specific checking behaviours, and mirrored patterns of use found by in chapter four, which defined a smartphone check as any usage under fifteen seconds. Likewise, the same definition of a smartphone check is used for this analysis. On average participants checked their phone 58.06 times daily [*SD* = 38.75].

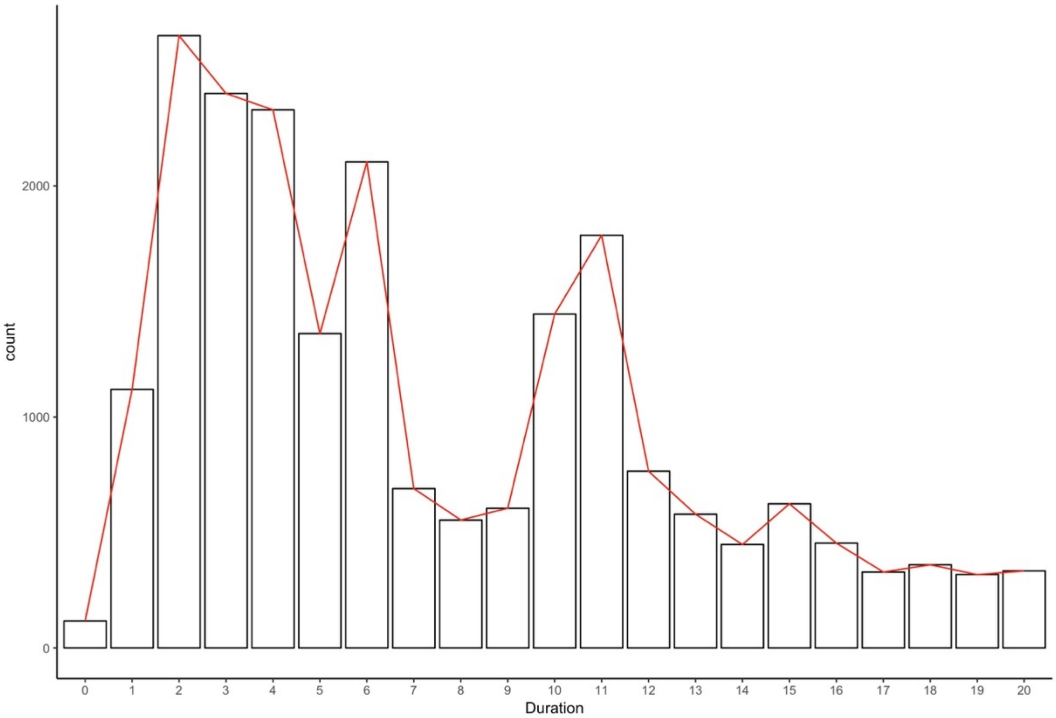

Figure 5.4. A graph showing the frequency of uses that lasted specific durations in one second bins.

552 unique applications were used across all 46 participants across the week. Aggregate daily statistics for individual applications were calculated by using the means across the seven days for hours of use, pickups and checks. Across the seven days, Snapchat was the most used application in terms of time, having an average use of 0.37 hours per day [SD = 0.53], followed by Facebook [M = 0.36, SD = 0.30], Facebook Messenger [M = 0.25, SD = 0.24], Instagram [M = 0.23, SD = 0.28], and then YouTube [M = 0.15, SD = 0.27]. However, many applications were not used consistently across the sample. Out of the 552 unique applications, 337 applications were only used by one participant. Overall, 81% of documented applications were used by three or less participants.

5.2.2.5. Nomothetic Analysis

Several correlations were performed to explore if there were any relationships between smartphone use and personality/demographics. Many of the daily smartphone variables did not conform to a normal distribution when conducting Shapiro-Wilk tests. As such we followed Bishara and Hittner (2017) recommendations and conducted Spearman correlations with Fieller, Hartley and Pearsons (1957) variance when calculating 95 % confidence intervals as these are robust against non-normality. Pearson correlations with 95 % bias-corrected and accelerated confidence intervals based on 100,000 bootstrapped samples were also conducted, as these have relatively good coverage when providing confidence interval estimates on non-normal data (Bishara & Hittner, 2017). This bootstrapping method also controlled for type one errors when making multiple comparisons. As such the two analysis were used in tandem, and results were only considered reliable if both analysis shared the same conclusions.

HEXACO Personality Analysis

First, we explored whether there were any relationships between average daily screen time, average daily pickups, and average daily checks with the six HEXACO traits. No significant relationships were found between conscientiousness, emotionality, extraversion, honesty-humility, and openness-to-experience with average daily screen time, across both Pearson and Spearman correlations (all *p*'s > .05). Agreeableness had a significant negative relationship with average daily screen time when conducting Spearman correlations [$\boxed{r_s}$ (44) = -.30, *p* = .04, 95% *CI* = -0.55, -0.00] but this result was not replicated in the Pearson analysis [$\boxed{r}$ (44) = - .28, *p* = .06, 95% *CI* = -0.51, 0.01]. Daily pickups had a negative correlation with openness-to-experience when conducting Pearson correlations [$\boxed{r}$ (44) = - .31, *p* = .04, 95% *CI* = -0.56, -0.01], but this finding was not replicated in the Spearman analysis [$\boxed{r_s}$ (44) = -.27, *p* = .07, 95% *CI* = -0.53, 0.03]. Daily pickups were not significantly related to any other personality trait across both Spearman and Pearson correlations (all *p*'s > .05). When examining daily checks, no significant relationships were found across all personality traits when conducting both Spearman and Pearson correlations (all *p*'s > .05). Hypothesis one is therefore rejected as personality was not found to reliably correlate with daily hours of use, pickups, and checks.

Following this, it was of interest to examine whether each of the six personality traits correlated with average app daily checks, average app daily pickups, and average app daily screen time (Hrs) using the same protocol as above. Due to the high amount of missing values, only applications used by 50% or more participants were examined. This meant that 29 applications were assessed in the analysis (see Table 5.3.). In addition, correlations were also conducted between each of the six personality traits and average daily phone unlocks, average daily app loads, average daily unique apps, No. installed apps, median daily inactivity, average daily screen off's, average screen on duration (secs), and average inactivity duration (secs). Across the 1140 comparisons, table 5.4. shows findings that were significant across both Spearman and Pearson analysis, in instances where the confidence interval did not cross zero. Predominately, no significant relationships were found. This further suggests the rejection of hypothesis one due to the absence of significant relationships.

Table 5.3. The proportion of the sample which used each app across the week and their daily descriptive statistics.

App Name	% sample used the app	Average Daily Screen Time (Hrs)	*SD*	Average Daily Pickups	*SD*	Average Daily Checks	*SD*
Android System	97.82	0.04	0.05	7.29	7.97	5.98	6.27
Messenger	97.83	0.25	0.24	34.69	42.21	23.20	29.02
Camera	95.66	0.02	0.05	2.08	1.86	1.28	1.19
Clock	95.65	0.02	0.03	3.62	3.23	2.71	2.68
System UI	95.65	0.08	0.17	25.04	27.75	23.70	27.18
Google Play Store	93.48	0.01	0.02	1.59	2.05	1.05	1.50
Maps	93.48	0.03	0.05	2.19	2.61	1.36	1.82
Phone	89.13	0.06	0.09	2.31	2.69	1.21	1.71
YouTube	89.13	0.15	0.27	2.14	3.28	0.87	1.30
ActivityLog	84.78	<0.01	<0.01	1.08	0.97	1.06	0.95
Facebook	84.78	0.36	0.30	17.25	17.18	6.87	7.23
appUsageLogger	82.61	<0.01	<0.01	1.33	1.13	1.30	1.11
Contacts	82.61	0.01	0.02	1.54	2.02	1.24	1.79
Package installer	82.61	<0.01	<0.01	0.54	0.80	0.52	0.80
Google	78.26	0.03	0.05	4.60	5.56	2.89	3.59
Settings	78.26	0.01	0.01	1.47	1.72	1.06	1.27
Chrome	76.09	0.13	0.15	6.21	6.70	2.21	2.98
Calendar	73.91	0.01	0.01	1.19	2.00	0.73	1.38
Gmail	73.91	0.03	0.04	3.98	6.85	2.59	5.19
Instagram	73.91	0.23	0.28	12.22	14.54	4.64	5.45
Calculator	69.57	<0.01	<0.01	0.38	0.47	0.25	0.37
Messages	69.57	0.03	0.04	4.20	5.61	2.51	3.29
Snapchat	69.57	0.37	0.53	25.39	33.29	11.93	16.39
x	69.57	0.03	0.16	1.08	1.40	0.92	1.27
WhatsApp	65.22	0.10	0.20	11.74	28.37	6.85	17.89
Outlook	63.04	0.03	0.04	3.38	4.30	1.99	2.48
Google Play Services	58.70	0.01	0.04	1.22	2.62	1.01	1.96
Spotify	56.52	0.03	0.05	5.17	8.83	3.46	6.17
Gallery	52.17	0.01	0.02	1.62	2.34	0.93	1.47

Table 5.4. Significant correlations between daily phone variables and personality variables.

Phone Variable	Personality Variable	Pearson			Spearman Rank		
		r	*p*	BCa 95% *CI*	r_s	*p*	95% *CI*
Android System Hours	Extraversion	.35	.02	0.14, 0.53	.30	.04	0.01, 0.55
Chrome Pickups	Agreeableness	.31	.03	0.02, 0.54	.38	.01	0.10, 0.61
Contacts Checks	Openness	-.40	.01	-0.64, -0.16	-.41	.01	-0.63, -0.12
Contacts Pickups	Openness	-.35	.02	-0.61, -0.08	-.34	.02	-0.58, -0.04
Facebook Hours	Conscientiousness	.34	.02	0.12, 0.54	.30	.04	0.00, 0.55
Gallery Checks	Openness	-.32	.03	-0.54, -0.11	-.33	.02	-0.57, -0.04
Gallery Hours	Openness	-.34	.02	-0.51, -0.09	-.35	.02	-0.59, -0.06
Gallery Pickups	Openness	-.35	.02	-0.57, -0.12	-.37	.01	-0.60, -0.08
Google Play Services Checks	Agreeableness	.32	.03	0.09, 0.47	.39	.01	0.10, 0.61
Google Play Services Pickups	Agreeableness	.30	.05	0.06, 0.45	.37	.01	0.08, 0.60
Messenger Checks	Emotionality	.32	.03	0.02, 0.47	.31	.04	0.01, 0.56
Outlook Checks	Agreeableness	.40	.01	0.14, 0.60	.30	.04	0.00, 0.55
Package Installer Hours	Extraversion	-.48	<.001	-0.70, -0.25	-.49	<.001	-0.69, -0.22
Package Installer Hours	Agreeableness	-.35	.02	-0.57, -0.04	-.44	.001	-0.66, -0.17
Package Installer Pickups	Extraversion	-.30	.04	-0.51, -0.05	-.37	.01	-0.60, -0.07
Phone Hours	Conscientiousness	.35	.02	0.12, 0.54	.37	.01	0.08, 0.60
Settings Hours	Conscientiousness	.32	.03	0.07, 0.50	.35	.02	0.05, 0.58

Age Analysis

Further, it was of interest to explore whether smartphone variables could predict age. It was predicted that as age increased, smartphone use would either increase or decrease. To begin, correlations were conducted between age and all the smartphone variables listed in table 5.2., with the addition of daily checks, pickups and hours of use across the 29 applications.

Table 5.5. shows findings that were significant across both Spearman and Pearson analysis, in instances where the confidence interval did not cross zero. Notably as age increased, the length of inactivity between phone uses increased across both Pearson [$r(44) = .75$, $p < .001$, 95% $CI = 0.47, 0.93$] and Spearman correlations [$r_s(44) = .61$,

p <.001, 95% CI = 0.38, 0.77]. Also, as age increased there was a significant decrease in average daily checks, average daily pickups, average daily hours of use and average daily phone unlocks (see table 5.6.). This suggests an overall trend; as age increases, average general smartphone use decreases. In accordance, average daily hours spent on Facebook Messenger and Snapchat also significantly decreased as age increased (see table 5.5.). Across the board, these findings support hypothesis three, which posited that age would predict smartphone usage behaviours.

Table 5.5. Significant Correlations between Age and Daily Phone Variables

Phone Variable	Pearson			Spearman Rank		
	r	*p*	BCa 95% CI	*r*	*p*	95% CI
Average Daily App Loads	-.35	.01	-0.55, -0.07	-.33	.03	-0.57, -0.03
Average Daily Screen Offs	-.53	<.001	-0.66, -0.34	-.52	<.001	-0.71, -0.26
Average Daily Phone Unlocks	-.43	<.01	-0.59, -0.23	-.34	.02	-0.58, -0.05
Average inactivity Duration (Secs)	.75	<.001	0.47, 0.93	.61	<.001	0.38, 0.77
Average Daily Messenger Hours	-.32	.03	-0.45, -0.10	-.38	.01	-0.61, -0.10
Median Daily Inactivity (Hrs)	.47	.001	0.21, 0.66	.46	.001	0.19, 0.67
Average Daily Checks	-.47	<.001	-0.61, -0.28	-.47	<.001	-0.68, -0.20
Average Daily Pickups	-.53	<.001	-0.66, -0.34	-.52	<.001	-0.71, -0.26
Median Daily Screen Time (Hrs)	-.41	<.01	-0.64, -0.13	-.45	<.01	-0.66, -0.17
Average Daily Snapchat Checks	-.36	.02	-0.46, -0.23	-.49	<.001	-0.69, -0.23
Average Daily Snapchat Hours	-.36	.01	-0.46, -0.24	-.55	<.001	-0.73, -0.30
Average Daily Snapchat Pickups	-.37	.01	-0.48, -0.25	-.51	<.001	-0.70, -0.25
Average Daily System UI Pickups	-.31	.04	-0.42, -0.16	-.44	<.01	-0.66, -0.17

Gender Analysis

Finally, smartphone use was predicted to be indicative of a person's gender. To compare if there were differences in smartphone use between men and women, several Wilcoxon rank-sum tests were conducted with gender as the independent variable and each smartphone variable (listed in table 5.2.) as dependent variables (including daily checks, pickups and hours of use across the 29 applications). Findings showed that women 'picked up', checked, and spent longer amounts of time on the Gallery application than men (see table 5.6.). In addition, across hours, pickups and checks men used the Google Play Store and the Google Play Services significantly more than women. Furthermore, men used a greater variety of applications each day and had more installed applications on their phone than women (see table 5.6.). Women spent more time on Facebook and had greater Messages checks and Messages pickups than men (see table 5.6.). Lastly, men had significantly higher amounts of Google Chrome checks and significantly lower Calculator pickups than women. Consequently, these results support hypothesis two stating differences in smartphone use would occur between men and women.

Table 5.6. Significant Wilcoxon Rank-Sum Tests Showing Differences Between Men and Women and Daily Phone Variables.

Phone Variable	*W*	*p*	*r*	Men *M*	Women *M*
Average Daily Unique Apps	118	.03	-.32	29.46	25.22
Calculator Pickups	286	.04	-.31	0.18	0.45
Chrome Checks	124.5	.04	-.30	4.02	1.58
Facebook Hours	299	.02	-.35	0.18	0.43
Gallery Checks	303	< .01	-.39	0.18	1.19
Gallery Hours	314.5	< .01	-.43	0.00	0.02
Gallery Pickups	310	< .01	-.41	0.30	2.09
Google Play Services Checks	108.5	.01	-.37	2.56	0.46
Google Play Services Hours	103	< .01	-.39	0.03	0.00
Google Play Services Pickups	101	< .01	-.39	3.24	0.50
Google Play Store Checks	92.5	< .01	-.41	2.24	0.63
Google Play Store Hours	65	< .001	-.51	0.02	0.01
Google Play Store Pickups	75.5	.001	-.47	3.40	0.95
Messages Checks	287	.04	-.31	0.89	3.08
Messages Pickups	288.5	.03	-.32	1.45	5.17
No. Installed Apps	70.5	<.001	-.49	103.17	71.21

5.2.2.6. Ideographic Analysis

Consistency in Checking Behaviours

Results of the descriptive statistics showed that 43.54% of smartphone uses were under 15 seconds in duration and that the frequency of phone uses which lasted for a specific length of time could be plotted in a histogram using all participant data in the sample (see Fig 5.4.). The peaks of use lasting specific durations in Fig 5.4. mirrored those found in a separate sample in chapter four. This led to the definition of a smartphone check being any use which lasts for under 15 seconds in duration. Consequently, it may be possible that these peaks of use represent average population smartphone checking behaviours due to the consistencies found across two separate samples. Historically, whenever norms are established, exploring how people deviate from this norm is considered representative of their individual differences (Clark, Lawlor-Savage, & Goghari, 2016). Following this line of thought, it was considered that people may have distinctive checking histograms (see Fig 5.6.), which are unique to themselves and are consistent. The following section details the exploratory analysis aimed at answering this question.

‘Checking histograms’ solely display a person’s phone uses under 15 seconds long in one second bins. In other words, visualising the frequency of usage durations that lasted one second, two seconds or three seconds long etc. Exploring uses in one second bins for any phone use under 15 seconds long, generates 15 frequencies to be plotted per person (see Fig 5.6.). This series of numbers can also be used in classification algorithms to identify users from their unique sequence. If people have unique smartphone checking behaviours that are consistent over time, then the shape of daily ‘checking histograms’ from the same user should be consistent across days of the week (see Fig 5.7.). Consequently, ‘checking histograms’ and their corresponding series of numbers were computed individually for each day of the study, per person.

To explore whether users could be classified from their individual ‘checking histograms’, a conditional inference forest (see chapter 3) was trained with the data from all 46 participants. Frequencies from six ‘checking histograms’, corresponding to the first six days in the study were used to the train the forest, and each of the 46 participants were coded as a different class to be predicted. Results from this training created a model which could classify individual smartphone users from six days of checking behaviours with 88% accuracy.

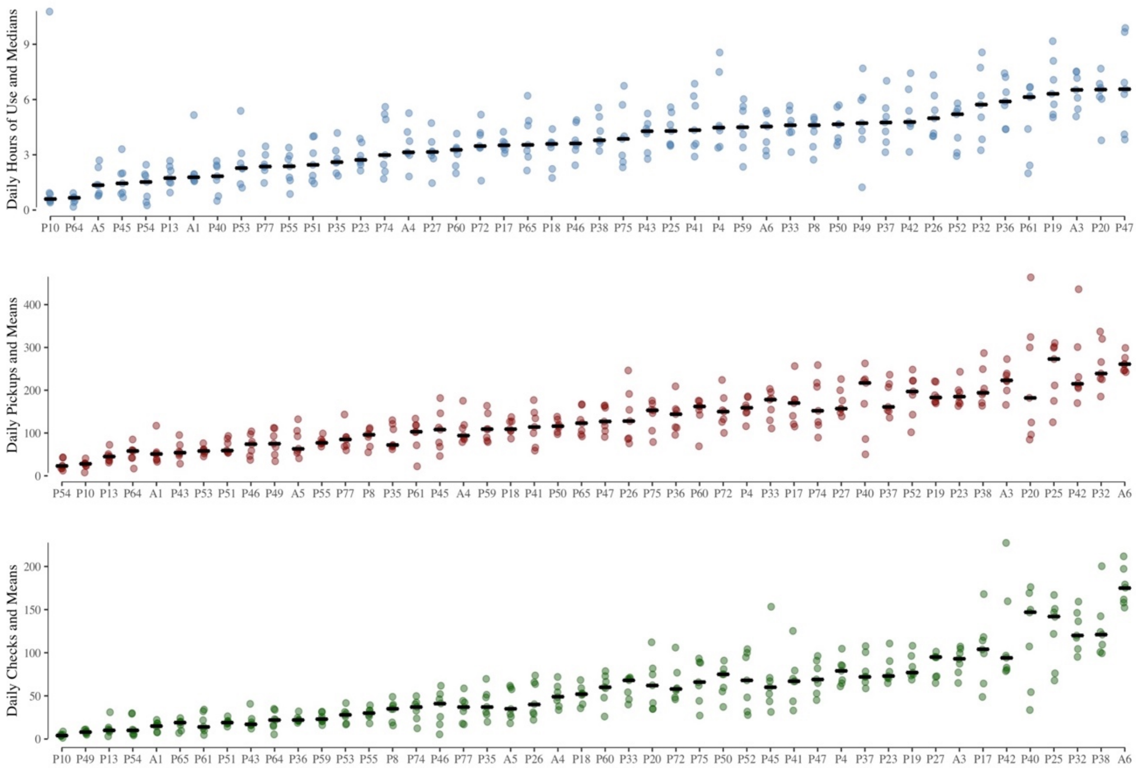

Figure 5.5. Plot showing each individuals consistency in their daily hours of smartphone use, checking behaviours and pickups across seven days of the study. The top figure represents hours of use, followed by daily pickups and daily checks. The relevant measure of central tendency is also plotted for each person across the plots. Medians were used for hours of use and means for daily pickups and daily checks.

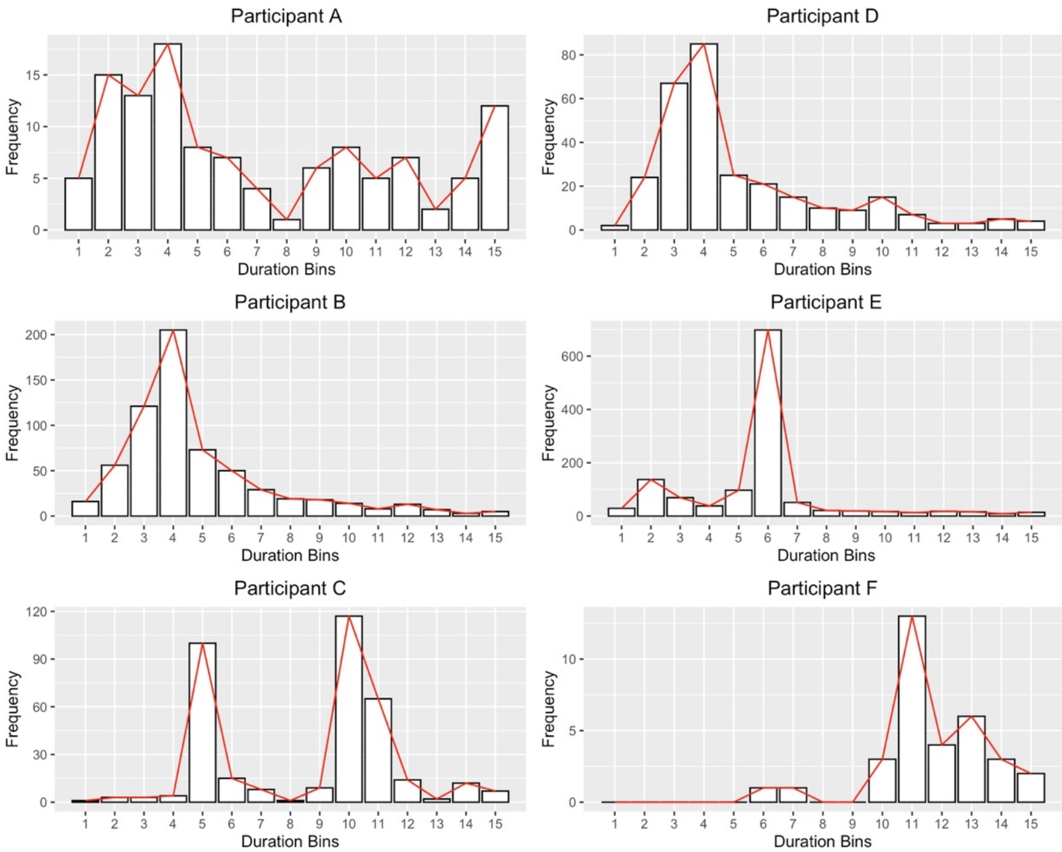

Figure 5.6. 'Checking histogram' showing checking frequencies of different participants using seven days of data in each graph.

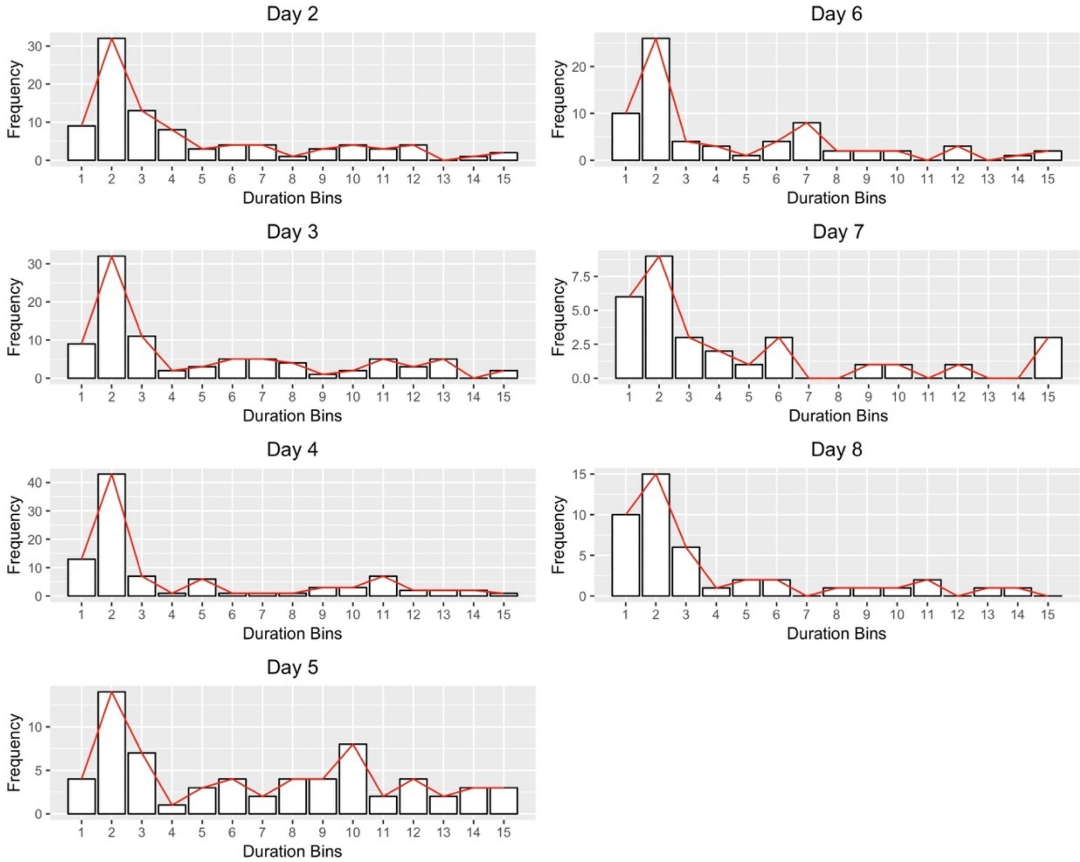

Figure 5.7. 'Checking histogram' showing the checking behaviours of one participant across individual days of the study.

However, it was of interest to see whether this model could predict a specific user from 'unseen' smartphone data from the last day of the study. The frequencies from peoples checking histograms which consisted of phone uses from the last day of the study were therefore used as test data. The random forest model was able to classify individual smartphone users from their last day of checking behaviours with 59% accuracy. When analysing the permutated importance of each duration bin, the durations which were most important for prediction was eleven seconds, followed by four seconds, six seconds, then ten seconds (see Fig 5.8.). Notably, these map onto the peaks of use in Fig 5.4. which plotted an average 'checking histogram' across all participants.

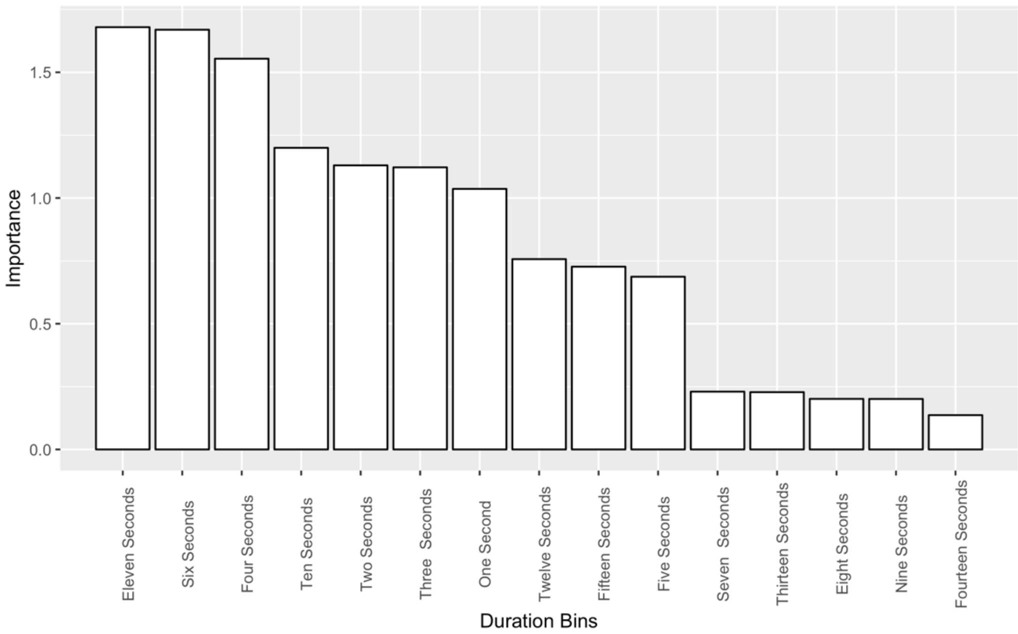

Figure 5.8. Graph showing the importance of each duration bin when predicting users from their checking behaviours.

Consistency in Application Usage Behaviours

The current dataset had 46 people with their longitudinal (seven full days) application data, and therefore a total of 322 days across all people. Following the procedure of Shoda, Mischel, & Wright, (1994), it was possible to convert the data within these 322 days into daily behaviour profiles of application use. Using the 29 most used applications (see table 5.4.), the purpose of this was to see if people's daily behavioural profiles of application use were consistent within the same participant and could therefore be used to identify a particular user within a 'crowd of data'.

Daily behavioural profiles were calculated for each of the three smartphone behaviours; daily application checks, daily application pickups and daily application time. This was achieved by finding the average daily usage across the 322 days for each application (see table 5.4). This list of 29 averages is considered the 'normative profile' of daily application use respectively for each smartphone behaviour. Following this, the standard deviations of usage across the 322 days were calculated individually for each smartphone behaviour across the 29 applications. This normative profile and list of standard deviations was then used to transform the data within each of the 322 days, for each smartphone behaviour as follows. The 29 scores in the normative profile was subtracted from the total usage values across the 29 applications respectively for that particular day and then divided by their standard deviations. This left 29 'normalised' application scores for each of the 322 days for each smartphone behaviour. Daily behavioural profiles of application use therefore represent how the usage of each application on that particular day deviates from the sample norm (see Fig. 5.9.).

To explore whether users could be classified from their daily behavioural profiles of application use, three conditional inference forests (see chapter 3) were trained separately for daily app checks behavioural profiles, daily app pickups behavioural profiles and daily app time behaviour profiles. Using data from all 46 participants, scores from six behavioural profiles, corresponding to the first six days in the study, were used to train each of the forests, and the 46 participants were coded as a different class to be predicted. The forest trained on six days of daily app time behavioural profiles could classify users from training data with 98.91% accuracy. The forest trained on six days of daily pickups behavioural profiles could classify users from training data with 99.63% accuracy. The forest trained on six days of daily checking behavioural profiles could classify users from training data with 99.28% accuracy.

Subsequently, the scores from participants behavioural profiles which consisted of phone uses from the last day of the study were used as test data. The 'daily app time' random forest was able to classify individual smartphone users from their seventh behavioural profile with 91.30% accuracy. The 'daily app pickups' random forest was able to classify individual smartphone users from their seventh behavioural profile with 95.65% accuracy. The 'daily app checks' random forest was able to classify individual smartphone users from their seventh behavioural profile with 91.30% accuracy. Therefore, the way in which a person's daily application usage deviates from the norm is unique to them and can be used to identify that user from 'anonymous data'.

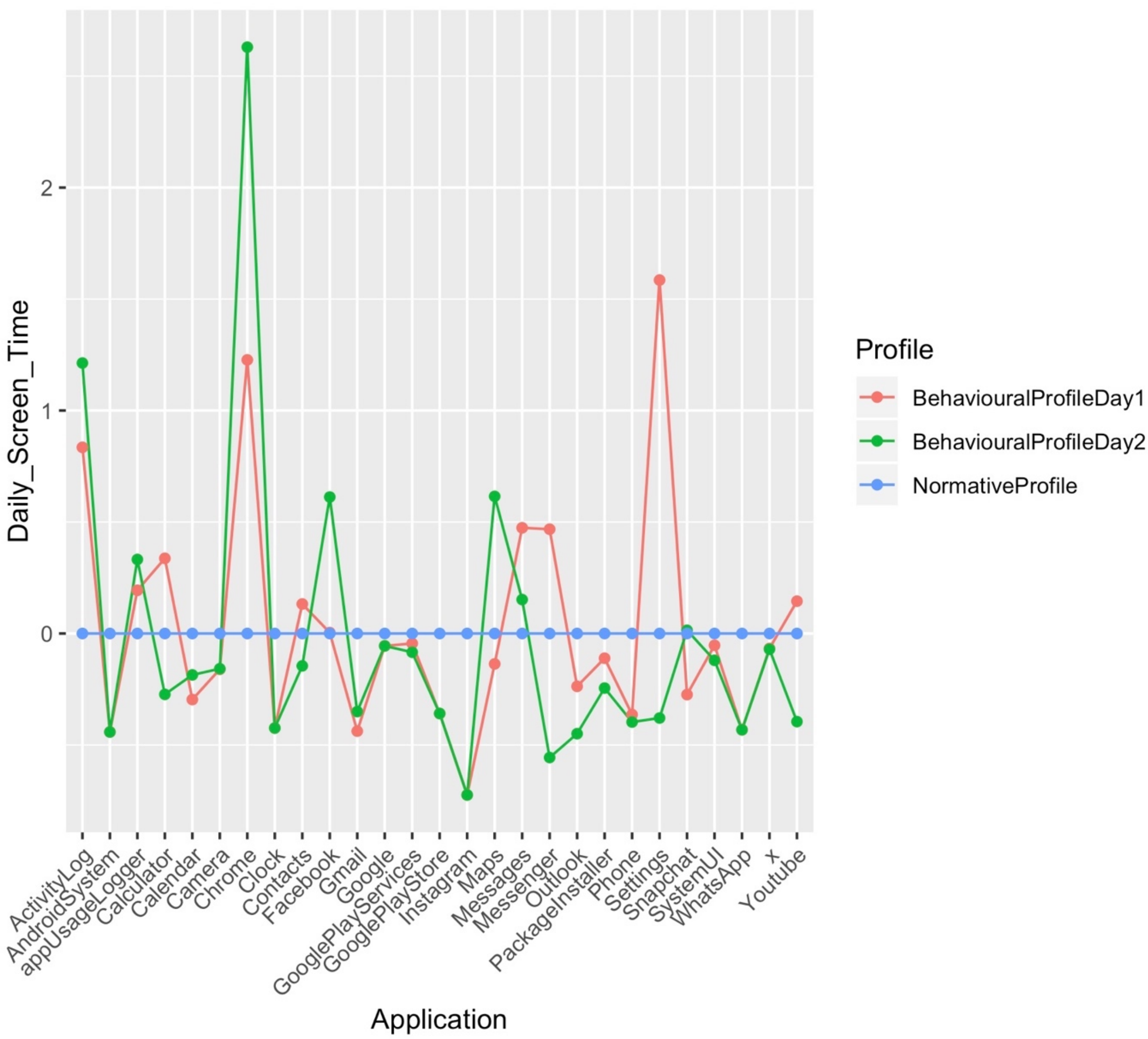

Figure 5.9. A graph plotting two behavioural profiles from the same person which represent their usage across two different days of the study. Scores have been 'normalised' around the normative profile. Therefore, it is possible to see how daily usage across the two days for each of the apps, deviates from the sample wide norm.

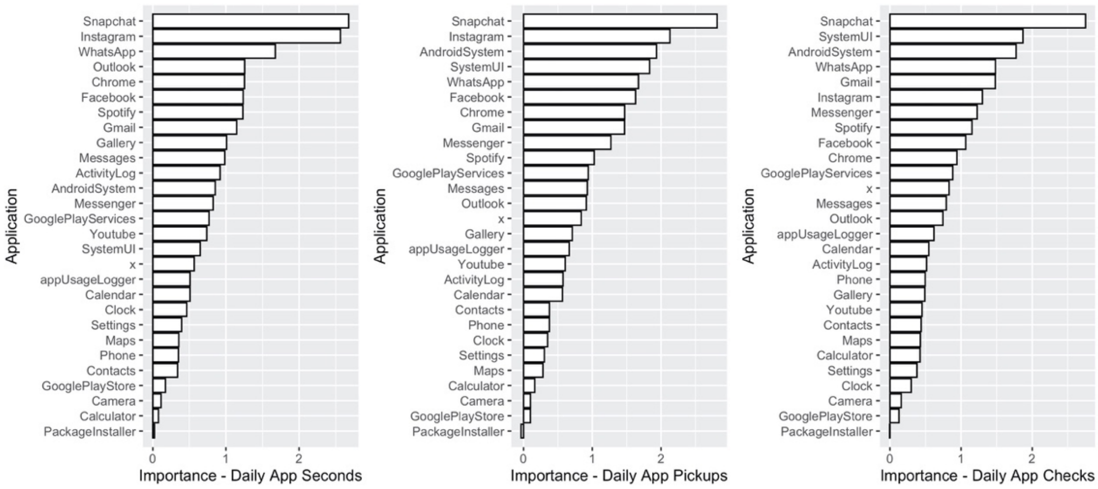

Figure 5.10. Graph showing the applications in the behaviour profiles which were most important for the prediction accuracy of each forest. This was done by permutating the 'normalised' scores within all the daily behaviour profiles for each application separately and measuring how this impacted the model's accuracy. From left to right, importance scores for the 'daily app time' random forest, 'daily app pickups' random forest, 'daily app checks' random forest.

5.3. Discussion

The aim of this chapter was to explore if objective logs of smartphone behaviours would be indicative of a person's individual differences, across both nomothetic and ideographic perspectives. The first was assessed across several hypotheses, predicting that personality traits, age and gender would be related to a person's objective smartphone behaviours. In opposition to Stachl et al. (2017), demographic variables such as age and gender were better predictors of objective smartphone use than personality traits. Overwhelmingly, findings showed that it is difficult to predict a user's personality traits from screen time and application usage measures alone, with significant findings being scarce across the numerous correlations conducted. This suggests that measuring personality traits from objective smartphone logs has its limitations.

However, by measuring personality ideographically, the analysis here showed that within-subject smartphone use was highly consistent and unique to the individual. This within person homogeneity and across person heterogeneity made it possible to identify users accurately from a single day of usage, when trained on just under one week of data. This was apparent for both daily checking and application usage behaviours. Consequently, the results here suggest that digital traces of smartphone usage data can be informative of a person's demographics and also reveal a person's unique 'smartphone usage personality' but is not informative of more general psychological constructs such as personality traits.

When examining differences in the users' demographics, age was a strong predictor of smartphone use. Notably as age increased, the time interval between phone uses and daily smartphone inactivity also increased. In accordance, the older a person was, the less time they spent on Facebook messenger, Snapchat, and general screen time. This is in line with previous findings which used self-report methodologies. For example, Kim, Briley, and Ocepek (2015) found a large negative correlation between age and smartphone use in a sample of 9482 individuals. Further, Elhai and Contractor (2018) found that smartphone usage frequencies had a negative correlation with age when utilising a six-point scale ranging from "Never" to "Very Often". The results from the present study add to these findings by showing that this relationship is also apparent when measuring smartphone use with objective logs. Notably effect sizes were greater than those reported in previous studies and the effect sizes differed dependent on the smartphone usage variable being assessed. For example, a large effect size was found when exploring the relationship between age and the time spent between phone uses (r = 0.75), whereas the effect size was medium when analysing the relationship between general screen time and age (r = - 0.41). These nuances are missed when using psychometric scales or usage estimates which only generate one score to capture overall smartphone usage patterns.

It is possible that as age increases, people's routines naturally gravitate towards reduced screen time and longer time intervals between uses. It might also be possible that people's motivations towards using their smartphone and the goals they wish to achieve via use may change with age, in line with the Technology Integration Model (chapter two). Analysing application use may be indicative of this change. For example, a previous study showed that older age was associated with increased use of

Chrome, Google play store, Twitter, WhatsApp, BBC News and eBay applications (OFCOM, 2018). Whilst these effects were not present here, the current data found that two other applications, namely Snapchat and Facebook messenger were used for less time by those who were older. Future research would benefit from assessing people longitudinally, to measure how smartphone use within the same person changes over the course of their life.

In addition, gender was found to predict differences in smartphone behaviours. In particular, women had greater Calculator pickups, Gallery hours, Gallery pickups, Gallery checks, Facebook hours, Messages checks, and Messages pickups than men. In contrast, men had increased usage when analysing Google Play Store hours, Google Play Store pickups, Google Play Store checks, Google Play Services hours, Google Play Services pickups, Google Play Services checks, number of installed applications, average daily unique applications, and Chrome checks. This partially supports prior self-report research showing that women used relational applications in greater amounts than men (Kim, Briley, & Ocepek, 2015; Anshari et al., 2016). Other log data would also support this view too, as men in a previous study spent longer on the Google Play Store and BBC news applications, whereby women spent longer on Facebook, Chrome, Instagram, YouTube, WhatsApp, Snapchat and Amazon Shopping (OFCOM, 2018). It is likely that men and women have different drivers and motivations behind smartphone use which is reflective in their choice of applications (see TIM model, Chapter 2). However, a simple digital trace, such as Google play store hours or number of installed applications is likely to predict gender with a high degree of accuracy.

On the other hand, smartphone use is less determinant of a user's personality than basic demographics such as age and gender. This is because significant findings from correlation analysis showed predominately no relationships between the two, and the small number of significant relationships may have been a product of the number of comparisons made. This is similar to (Montag et al., 2014) who found many comparisons between SMS/Calls logs and personality to be unreliable. Kambham et al. (2019) also conducted both Spearman and Pearson correlations and found no significant correlations between smartphone use and personality traits, with small correlations ranging between -0.31 to 0.26. Other research has also found that only extraversion out of the 'Big 5' can be predicted from objective smartphone data on a large sample of 730 students (Mønsted et al., 2018). One of the reasons for this can been explained by the 'abstraction issue' whereby, the more abstract a personality trait is, the more imprecise a personality measure will be at predicting that behaviour (Alison, Bennell, Mokros, & Ormerod, 2002). In other words, personality traits may be so far removed from objective smartphone behaviours due to their abstraction that relationships do not occur between the two. This is in contrast to self-report research which often shows a positive relationship between smartphone scales and personality (Kim, Briley, & Ocepek, 2015; Anshari et al., 2016; Tan, Hsiao, Tseng, & Chan, 2018; Roberts, Pullig, & Manolis, 2015). It is possible that self-report to self-report comparisons are less removed from each other in terms of abstraction than self-report to behaviour comparisons. Consequently, this conceptual distance between self-report and behaviour may in part explain why personality traits are difficult to predict from objective smartphone usage.

Alternatively, it is possible that the smartphone logs collected here do not capture nuances in behaviour such as what a person says in applications or what websites they visit which may be more indicative of personality. Furthermore, whilst trait approaches have utility by describing how a person will generally behave across situations through measuring only a few broad traits, this might make predicting actual behaviour more difficult due to this abstraction. Consequently, it has been argued that defining someone via their personality traits may be too restrictive as it limits individual differences to a few dimensions (Hinds & Joinson, 2019). It has even been proposed that through the exploration of digital footprints, that are removed from self-report assessments of personality, that researchers could find unique patterns of behaviour that are divorced from personality trait theories all together (Hinds & Joinson, 2019).

In line with this, a promising avenue of research is understanding people's unique smartphone behaviours, which appear to be consistent and distinct over time. Notably, assessing the durations of a person's smartphone behaviours under 15 seconds long can predict individual users from a set of participants with ~60% accuracy. Like chapter four, this finding is further evidence that a person's smartphone checking behaviours are habitual in nature, having consistencies across days in the study. However, additional insights have been found regarding the consistency of application usage behaviours. Notably how people's daily patterns of application usage deviate from a 'sample norm' is highly reflective of their unique 'smartphone use personality'. The findings here showed participants were using the same applications in consistent ways across the seven days of the study, whereby behaviour profiles of daily application pickups, daily application checks, and daily application time across 29 applications could identify an individual user with > 90% accuracy. This is in line with the Technology Integration Model (Chapter 2) which suggests over time people use technology repeatedly to satisfy the same motivations in the same contexts. Whilst much research on individual differences examines trends in personality traits and demographics across groups of people, this finding suggests that taking more of an ideographic approach can also provide insights into how smartphone behaviours can be indicative of its user. When applied to security settings, these results posit that people leave behind a recognisable trace of themselves when using technology, which may not reflect broad traits, but can identify a user like a 'digital fingerprint'.

A potential limitation concerns the sparsity off application usage data. Out of the 552 unique applications, 337 applications were only used by one participant. Therefore, 81% of documented applications were used by three or less participants. Similarly, Stachl et al. (2017) also found a great diversity of application use, whereby 137 participants used 2835 unique applications across a 60-day period. This was partially resolved in this chapter by only examining application use data from applications that were used by 50% of people or more. This was done in a similar manner to Chittaranjan et al., (2013) who only chose to analyse months which contained some use of the application in question. Whilst this sparsity may need controlling for when making personality trait predictions based on smartphone use, the uniqueness of people's application use might reveal unique insights when assessed ideographically. Therefore, future research could analyse how 'less popular applications' through either installed applications, or application usage across a pre-defined period of time could be used to define an individual's characteristics.

Furthermore, it can be argued that the sample size in this study was small, and therefore relationships with smaller effects may have not detected. However, this research is in its preliminary stages, whereby objective methods are just starting to be explored, and as a result there were unanticipated technical issues which reduced our sample from 80 to 46. It is possible that future work can integrate what was learnt in this study to mitigate these issues and gain a larger sample size. This includes trying to find more work arounds for Android's 'dose mode', which can stop applications from running in the background for battery saving reasons. Notably, the severity of this disruption depends on the smartphone brand, and it was found during data collection that Samsung phones were less affected by this. Therefore, future work could recruit users of brands which are less impacted by 'dose mode'. Finally, the objective smartphone data had a strong positive skew. Other researchers have dealt with this by performing a log transformation on the smartphone data (Chittaranjan et al., 2013). We instead followed recent recommendations to accurately model non-normal data with the considerations of confidence intervals and compared findings across two algorithms (Bishara & Hittner, 2017). These tighter controls on type one errors may also explain the minimal comparisons which were found to be reliable in comparison to (Chittaranjan et al., 2013).

To conclude, the findings of this chapter suggest it is difficult to predict personality traits from a user's screen time and application usage alone. However, it was possible to predict basic demographic details such as age and gender from variables such as smartphone inactivity and application use. This suggests a shift in predicting personality traits from smartphone data to other individual differences, as these may be more informative of a person's characteristics. Others have proposed that the future of personality prediction could move away from self-reported traits entirely, and measure user characteristics though distinct digital traces, such as the ideographic analysis conducted within this chapter (Hinds & Joinson 2019). Consequently, research into assessing individual differences from smartphone use is still in its infancy but with a promising future, as several research avenues are yet to be explored. Next, chapter six investigates people's health and wellbeing characteristics, to ascertain how these relate to digital traces of smartphone use.

Chapter 6

Quantifying smartphone ‘use’: Choice of measurement impacts relationships between ‘usage’ and health.

The following chapter forms part of the publication: Shaw, H., Ellis, D. A., Geyer, K., Davidson, B. I., Ziegler, F. V., & Smith, A. (2020). Quantifying Smartphone "Use": Choice of Measurement Impacts Relationships Between "Usage" and Health. *Technology, Mind, and Behavior, 1, 1-15.* https://doi.org/10.1037/tmb0000022

6.1. Introduction

In the previous chapter, how objective smartphone use was related to personality traits and demographics was explored in detail. Notably, when making personality predictions from smartphone usage measures, findings from self-report research methodologies were not always aligned with those found with objective measures. Therefore, it is possible that the relationship between other individual differences and smartphone use might change dependent on measurement. This would be particularly problematic when understanding how smartphone use is predictive of individual differences such as physical and mental health.

To elaborate, smartphones are primarily used for connecting people in a variety of personal and occupational settings. While the benefits of interpersonal communication are well-established (Berkman et al., 2000), most research concerning the relationship between communication technology and health has focused on 'negative consequences' of smartphone use and screen time with a strong focus on mental health (Elhai, et al., 2017), and sedentary behaviours (Zagalaz-Sánchez, et al., 2019). Often referred to as 'problematic smartphone use' or 'smartphone addiction' (Elhai et al., 2017), these refer to the perceived undesirable side-effects of use, which are mirrored in public discourse (Genc, 2014; Yang, Asbury, & Griffiths, 2019). However, there is a growing acknowledgement that the majority of research linking any screen time behaviours to health outcomes are themselves problematic (Science and Technology committee, UK Gov, 2019). For example, a growing number of academics have argued that research needs to address issues with measurement (Ellis, 2019), theory (Orben, 2018; Shaw, Ellis, & Ziegler, 2018), analysis choices (Orben & Przybylski, 2019), and prioritise high-quality designs to better understand genuine benefits or harms (Coyne, et al., 2019; Heffer, et al., 2019). This may, in part, explain the lack of a coherent academic position regarding the impact of smartphone use on wellbeing, and is troublesome when it comes to justifying the existence or effectiveness of interventions that aim to reduce usage. This chapter specifically investigates whether the relationship between smartphone use and health changes noticeably as a result of how smartphone use is conceptualised and measured.

6.1.1. Psychological Well-being

Survey research has repeatedly linked increased smartphone screen time to lower psychological wellbeing (Twenge, Martin, & Campbell, 2018). However, many have noted that smartphone use is rarely measured directly, despite objective data being readily available from devices themselves (Ellis, et al., 2019; Twenge, 2019). Moreover, in recent years, concerns regarding 'overuse' have led to an abundance of usage scales being created to measure new constructs, including: 'addiction', 'nomophobia', and 'problematic use' (Ellis, 2019; Thomée, 2018). Specifically, when using problematic smartphone use scales, research consistently links higher scores with greater mental health symptomology, however these relationships seem to either dissipate or lessen when collecting duration estimates of use or objective logs (Elhai et al., 2017; Harwood et al. 2014; Rozgonjuk et al., 2018; Katevas, Arapakis, & Pielot, 2018;Vahedi & Saiphoo, 2018). Thus, understanding when and why these inconsistencies occur remains essential.

6.1.2. Physical Health

Beyond psychological impacts associated with usage, research has also linked greater smartphone use with increased sedentary behaviours (Lepp, et al., 2013; Zagalaz-Sánchez et al., 2019). Accordingly, people report that 87% of all phone use occurs while seated (Barkley & Lepp, 2016), and similarily, 90.9% of users report that they typically are sitting when using their smartphone (Xiang et al., 2020). Thus, it has been proposed that increased smartphone use lowers energy expendenture due to sedentary behaviours, and it is this mechanism, which results in greater body fat and higher rates of obesity (Hamilton, Hamilton, & Zderic, 2007; Kim, Kim, & Jee, 2015). However, while 9 out of 14 articles in a recent systematic review showed a negative relationship between smartphone use and physical activity, none of the articles measured smartphone use objectively via logs from the device itself (Zagalaz-Sánchez et al., 2019). Instead, people self-reported the duration and frequency of their smartphone behaviours, which is widely documented to only have medium-to-large correlations with actual usage (see chapter four; Andrews et al., 2015; Boase & Ling, 2013; Parslow, Hepworth, & McKinney, 2003; Ellis et al., 2019; Kobayashi & Boase, 2012; Lee, et al., 2017; Vrijheid et al., 2006). Therefore, research linking physical activity or sedentary behaviours to smartphone use is also scarce and yet to be examined precisely using objective logs.

6.1.3. Conceptualising Usage

When understanding mental health relationships, more nuanced approaches suggest that how users think about and appraise their own smartphone usage is uniquely related to wellbeing and can be considered separately from objective use of the device itself. For example, a recent study found no evidence linking objective use of social applications to momentary wellbeing (Johannes et al., 2019). However, they did observe that the more positively people felt about their technology-mediated interactions in the past half hour, the better they felt in the current moment (Johannes et al., 2019). In addition, when assessing email use in occupational settings, stress levels increase when a person perceives their usage to be greater or lower than desired (Stich, et al., 2019). Thus, in line with the technology integration model, this suggests that people aim to regulate technology usage as they would with other everyday behaviours including for example, social affiliation (see chapter two; O'Connor and Rosenblood, 1996). Negative or positive appraisals may occur dependent on whether a person has been able to achieve their preferred amount of usage (O'Connor and Rosenblood, 1996; Stich, et al., 2019). Thus, it is plausable that the way people percieve their smartphone usage behaviours (e.g., a belief that their smartphone use is excessive) may drive the relationships with mental health, seperately from usage itself.

While there is no consensus regarding how smartphone usage or screen time should be conceptualised or measured, documenting 'usage' is of interest to many (Ellis, 2019). Researchers however, continue to conflate the measurement of smartphone usage with assessing an individual's appraisal of use. For example, defining or measuring problematic smartphone use (PSU) in relation to 'overuse' or 'excessive use’ is prevalent in many articles (Elhai & Contractor, 2018; Elhai, et al, 2020; Kim, 2017; Yang et al., 2019). This has foundations in the Behavioural Addictions framework, where tolerance is a key component (e.g., the need to increase use over time to get the same ‘fix’) (Billieux, Maurage, et al, 2015; Elhai et al., 2017; Kim, 2017). Hence, it is not surprising to find questions such as *“Using my smartphone longer than I had intended”*, and *“Having tried time and again to shorten my smartphone use time but failing all the time”* in problematic usage scales (Kwon et al. 2013). However, agreeing with these statements only shows that a person is negatively appraising their smartphone use, and is not a measure of frequency or screen time in itself. Correspondingly, research that has attempted to quantify the relationship between problematic usage scales and objective logs report many small-to-medium effect sizes (see chapter four), and exploratory factor analysis research shows that PSU scores do not cross-load with factors representing actual usage (Davidson, Shaw, & Ellis, 2020). This evidence already suggests that people’s appraisals of their smartphone use and actual usage should be considered seperately.

In light of this unclear conceptualisation, it is important to distinguish between PSU as a psychological construct that appraises use, and smartphone usage as a behavioural variable, because it has implications for theory and treatment. For example, if negative associations with physical and mental health are driven entirely by usage appraisals, then providing interventions that focus on usage behaviours alone may not deliver any benefits (Loid, Täht, & Rozgonjuk, 2020).

6.1.4. The Present Study

Measuring the associations between health and smartphone use in different ways could generate radically different results when relying on different operationalisations: subjective estimates, objective logs, and psychometric scales. This chapter aims to understand this issue by collecting all three measures from the same participants. Specifically, it explored the question:

> *"Do problematic use scale scores generate larger associations with health when compared with estimates of usage or objective behaviour from the same users?*

Furthermore, it was examined whether increased smartphone use, measured via objective logs or estimates was related to poorer physical or mental health. This assessed the notion of 'overuse' separately from problematic use scales. Therefore, this chapter also asked:

> *"Can objective smartphone use (pickups and screen time) account for differences in mental health symptomatology or physical health?"*

These ideas were first investigated during exploratory analysis of 46 adults who completed all three measurements, alongside an assessment of their body composition and anxiety, depression, and stress symptomology. The results were then used to generate hypotheses regarding the influence of different usage measurements on effect sizes. A second study then acted as a replication and provided increased statistical power. All materials for both studies are located on the Open Science Framework (Shaw et al., 2018; https://osf.io/a4p78/).

6.2. Study one: How does health and wellbeing relate to different measures of smartphone use?

6.2.1. Measures

The participants, procedures, and ethics for this study are described in chapter five. This is because the present dataset is shared across the two chapters. For brevity, the focus of this chapter is to describe the health relationships with general smartphone use. Therefore, only the variables in this dataset that were related to this aim are described in this chapter. For further information on all the variables collected see (Shaw, et al., 2018; https://osf.io/a4p78/), and see chapter five for all personality and demographic variables collected.

Objective Smartphone Use

Objective smartphone data was collected for nine days using an application developed specifically for the project called Activity Logger (Geyer, 2018). This ran on Android devices and collected data to the resolution of one second. Activity logger was set up to listen to three events: the phone being turned on, the screen being activated, and the screen being turned off. Background operations then took this information, retrieved the current time stamp, and stored this in internal memory. This data file was then exported via the application and contained a list of records where a UNIX time stamp was paired with an event stating whether the screen was turning "ON" or "OFF". Source code for the application is available to download (https://osf.io/a4p78/).

Estimates of Smartphone Use

To gather estimates of daily smartphone screen time, participants were asked one question: "*Think back to days 2 - 8 of the study. On average, how many hours a day did you spend on your smartphone?"*. Participants responded in hours and minutes. To measure people's estimates of how many times a day they 'picked up' their device, participants were asked: "*Think back to days 2 - 8 of the study. On average, how many individual times did you use your smartphone a day? Think of these as individual pick-ups*."

Problematic Smartphone Use

Smartphone addiction was measured using the Smartphone Addiction Scale (SAS), which contained 33 items (Kwon et al., 2013). Participants rated the extent to which they agreed to several statements, for example "*Feeling pleasant or excited while using a smartphone*". Participants responded on a six-point Likert-Scale ranging from "Strongly Agree" (1) and "Strongly Disagree" (6). Higher scores indicated greater addiction risk. This scale was chosen because it is widely cited and correlates highly with a variety of other PSU measures, which all appear to measure the same construct (Ellis et al. 2019; Thomée 2018; Davidson, Shaw & Ellis, 2020).

Anxiety

Symptoms of anxiety were measured using the GAD-7 (Spitzer, et al. 2006) and included 7 items. Participants were asked "*how often in the last two weeks have you been bothered by…*" and responded on a four-point scale whereby 0 = "Not at all" and 3 = "Several Days". Using >10 as a cut-off point, the GAD-7 has been shown to have 89% sensitivity and 82% specificity with a diagnosis of general anxiety disorder (Kroenke et al., 2007).

Depression

Severity of depression was measured using the PHQ-9 (Kroenke, et al. 2001). Each of the nine questions related to a criterion mentioned in the DSM-IV for depression. Participants were asked "*how often in the last two weeks have you been bothered by…*" and responded on a four-point scale whereby 0 = "Not at all" and 3 = "Several Days". Using >10 as a cut-off point, the PHQ-9 has been shown to have 88% sensitivity and 88% specificity with a diagnosis of major depression (Kroenke et al., 2001).

Perceived Stress

The Perceived Stress Scale (Cohen, Kamarck, & Mermelstein, 1983) had 14 items which measured 'the degree to which situations in one's life are appraised as stressful'. Participants responded how often they felt a certain way on a 5-point Likert scale whereby 0 = "Never" and 4 = "Very Often". Participants were asked questions such as "*In the last month, how often have you felt that you were on top of things?*". Higher scores indicated greater perceived stress.

Objective Health Measures

Height was measured using a meter stick, with age and gender captured via self-report questions. This data was inputted as controls in subsequent bioimpedance analysis. Body composition was measured using the eight electrode Tanita MC-780MA body composition monitor. This provided an estimate of a person's body fat percentage, body mass index, and skeletal muscle mass percentage, using bioelectrical impedance measures. Bioelectrical impedance assessment using the Tanita MC-780MA was a good alternate to Magnetic Resonance Imaging and Dual Energy X ray absorptiometry (DEXA) which are costly, and time-consuming (Verney, et al., 2015). Notably, the Tanita MC-780MA produces body fat assessments which highly correlate with DEXA assessment ($r = .85$) providing concurrent validity (Verney et al., 2015).

6.2.2. Results

Data from this study is avaiable to download on the Open Science Framework (Shaw et al., 2018; https://osf.io/a4p78/).

6.2.2.1. Data processing

The median daily hours-of-use was calculated across days two to eight for each person to remove the influence of any extreme "Screen On" events that occurred if the phone battery depleted and the application did not log a 'Screen Off' event. Daily pickups (frequency of use) were averaged across days two-eight, in accordance with chapter four, study one. For the smartphone addiction scale, GAD-7, and PHQ-9, the responses were summed to create a total score for each scale. Specific questions within the perceived stress scale required reverse coding, and then an overall sum was created per person. See Table 6.1. for a list of the variables used in the analysis and their descriptives.

6.2.2.2. Exploratory Analysis

When collating all 46 participants' data together, smartphone use was highly skewed, as 54.44% of uses were under 30 seconds in duration, and 43.54% of uses were under 15 seconds in duration. Due to this skew, this chapter followed Bishara and Hittner (2017) recommendations and conducted Spearman Rank order correlations with Fieller, Hartley and Pearsons (1957) variance when calculating 95 % confidence intervals as these are robust against non-normality. To explore how differences in smartphone measurement may influence associations with health, Spearman correlations were conducted between all the health and smartphone variables (see Table 6.2.). Notably anxiety, depression, and, stress had significant positive correlations with smartphone addiction scores (all p's <.01), which did not occur with any other smartphone measure (see Fig. 6.1. for objective screen time specifically). In terms of effect sizes, smartphone addiction scores generated r_s equal to or larger than .39 with mental health variables, whereby estimates and objective variables were lower (all r_s<.2) (see Fig. 6.3.).

Table 6.1. Study 1 descriptives.

Health Variables	Mean	SD	α	Smartphone Variables	Mean	SD	α
Body Mass Index	24.84	5.86		Median Daily Screen Time (hrs)	3.74	1.60	.90
Body Fat %	26.97	8.86		Average Daily Pickups	133.18	63.52	.93
Skeletal Muscle Mass %	41.35	6.40		Daily Screen Time Estimate (hrs)	5.08	3.36	
Anxiety	6.13	5.56	.92	Daily Pickups Estimate	48.74	39.96	
Depression	6.57	5.25	.85	Smartphone Addiction Scale	90.09	21.20	.90
Stress	24.61	8.42	.87				

Table 6.2. Spearman correlations between smartphone and health variables from study 1.

Health Variable	Smartphone Addiction		Screen Time Estimate		Pickups Estimate		Median Daily Screen Time		Average Daily Pickups	
	Spearman r_s	Spearman 95% *CI*	Spearman r_s	Spearman 95% *CI*	Spearman r_s	Spearman 95% *CI*	Spearman r_s	Spearman 95% *CI*	Spearman r_s	Spearman 95% *CI*
Physical Health										
Body Mass Index	-.25	-0.51, 0.05	-.10	-0.39, 0.21	-.14	-0.42, 0.16	-.32*	-0.57, -0.03	-.39**	-0.62, -0.11
Body Fat %	.09	-0.21, 0.38	.18	-0.13, 0.45	-.01	-0.31, 0.29	-.01	-0.30, 0.29	-.12	-0.40, -0.18
Skeletal Muscle Mass %	-.06	-0.35, 0.24	-.14	-0.42, 0.17	.05	-0.25, 0.35	.06	-0.24, 0.35	.19	-0.11, 0.47
Mental Health										
Anxiety	.44**	0.17, 0.66	.11	-0.19, 0.40	.05	-0.25, 0.34	-.00	-0.30, 0.30	.11	-0.20, 0.39
Depression	.39**	0.11, 0.62	.19	-0.11, 0.47	-.05	-0.35, 0.25	.05	-0.25, 0.34	.08	-0.23, 0.37
Stress	.53***	0.27, 0.71	.18	-0.13, 0.45	.03	-0.27, 0.32	.00	-0.30, 0.30	.03	-0.27, 0.32

Notes: * significant at $p < .05$, ** significant at $p < .01$, *** significant at $p < .001$. Alpha's remain uncorrected for multiple comparisons

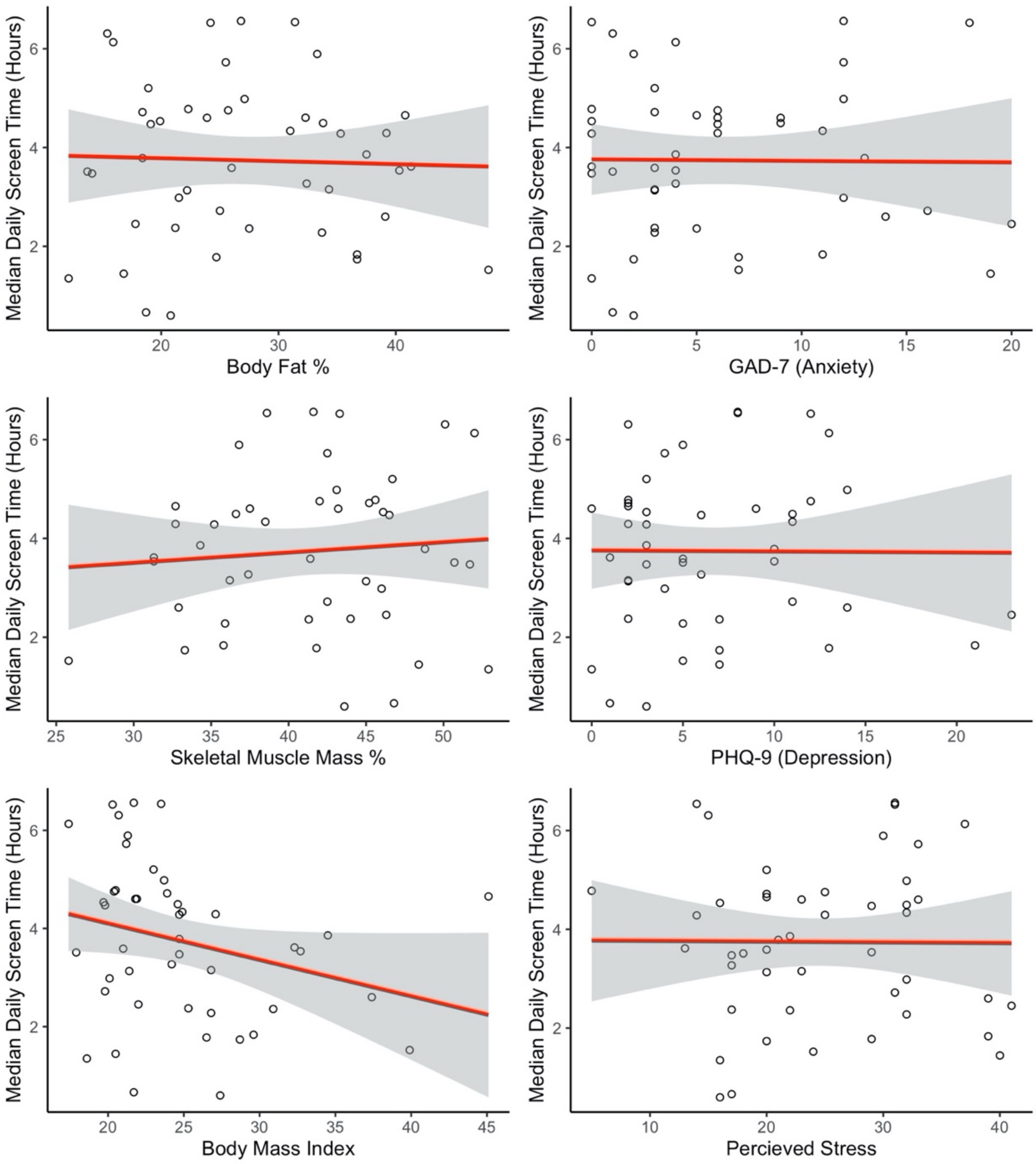

Figure 6.1. Scatter plots illustrating linear relationships between median daily screen time (Hours) and six health variables; body fat percentage, skeletal muscle mass percentage, body mass index, anxiety, depression, and stress. Regression line (red) illustrates linear relationship between each pair with 95% confidence interval (grey).

6.2.3. Discussion

In study 1, smartphone addiction was found to positively correlate with anxiety, depression, and stress measures. Pertinently, effect sizes quadrupled when measuring smartphone usage with a problematic usage scale in comparison to objective screen time and pickup measures. In line with prior work, people's appraisals of their smartphone usage had stronger relationships with mental health than self-reported frequencies of use (Vahedi & Saiphoo, 2018) or objective logs (Rozgonjuk et al. 2018). This suggests peoples' appraisals of their smartphone use (e.g., worries) are more pertinent to mental health symptomology than actual usage. Therefore, even within the same participants, a researcher could make different conclusions based on the measurement tool adopted. This is especially problematic when confounding the construct of problematic smartphone use with actual usage. Interestingly, findings showed that BMI reduced as daily screen time and pickups increased. While gravitating in the same direction, the effect size was smaller for correlations between actual usage and body fat percentage. Nevertheless, neither suggested the presence of any adverse effects between daily smartphone screen time and pickups on these measures of physical health.

These findings were marked as tentative until they could be replicated in a larger sample. This was examined in study 2, whereby identical mental health and smartphone measures were collected to match study 1. BMI was also reassessed, and the researcher took advantage of retrospective data collected on a user's device, including daily logs of steps, and daily logs of 'walking and running' distances. Based on previous findings, it was predicted that effect sizes of r_s > .3 would be found when comparing mental health relationships with problematic usage scales, and that lower effect sizes of r_s < .2 would be found when examining estimates of use and objective logs.

6.3. Study two: How does smartphone measurement type influence effect sizes between usage and mental health.

6.3.1. Methods

6.3.1.1. Participants

199 [137 women] participants, were recruited via Prolific Academic, from a subject pool of 24,117 iPhone owners. This pool contained predominately citizens from the United Kingdom and the United States. Participants had a mean age of 30.18 [*SD* = 9.46] and were paid £1.25 for their time. 42.71% of the sample were overweight or obese, and the average BMI across all participants was slightly higher than the recommended range [*M* = 25.17, *SD* = 5.38]. This was to be expected in a representative sample, as 52% of people have a BMI over 25 world-wide (WHO, 2018). A priori power calculation was performed which showed during two-tailed analysis a sample size of 192 participants was enough to detect small effect sizes of r_s ≥ .2 with a power of .8 when $\alpha = .05$.

6.3.1.2. Measures and Procedure

Once clicking the link to access the online questionnaire, participants were presented with study information and a digital consent form. If participants agreed to take part, they were then asked; "*Please estimate how many hours and minutes you spend on your phone each day*" and answered in hours and minutes. In addition, participants were asked: "*Please estimate how many times a day you pick up and use your phone*". After, smartphone addiction, anxiety, depression, and stress were then measured using the same scales as study 1.

Objective smartphone usage data was retrieved by utilising the Apple Screen Time feature that resides in modern iPhones. This study used the same methodology as reported in chapter four and extracted data retrospectively from the previous 7 days. In short, participants were prompted to find the 'Screen Time' graph and the 'Pickups' graph in Apple Screen Time settings and record for each day the number of pickups and screen time (in hours and minutes). For more details, see chapter four, study one.

After obtaining objective smartphone use data, the questionnaire asked people to input their health data. The Apple Health App automatically tracks users' daily steps and combined 'walking and running' distances. This historic data is accessible on a user's iPhone for the entire time they have owned their iPhone. When clicking on the 'Today' tab, participants had access to a calendar where they could view their activity for any past day. Daily steps were collected by asking participants to click on the calendar pages for dates in the past week and enter for each day the number of steps displayed. Daily 'walking and running' distances were collected by asking people to click on the calendar pages for dates in the past week and report the documented distance in either kilometres or miles. Participants were also asked if they owned a fitness tracker or a smartwatch and specified whether this device was synced to the Apple Health App. Lastly, participants were asked to report their age, gender, weight and height. They were given the option to answer in either metric (meters and centimetres / kilograms) or imperial measures (feet and inches / stones and pounds). At the end of the questionnaire, participants were debriefed, thanked for their time, and were then re-directed back to the Prolific Academic website.

All procedures received ethical clearance by the School of Psychology Research Ethics Committee at the University of Lincoln and complied with British Psychological Society ethical guidelines for internet mediated research (Hewson et al., 2013). Akin to study 1, the debrief provided websites where participants could access guidance regarding their mental health and were provided with details of 24-hour support lines. Participants could withdraw at any time before, during or up to two weeks after they completed the study by emailing the researcher.

6.3.2. Results

Data from this study is avaiable to download on the open science framework (Shaw et al., 2018; https://osf.io/a4p78/).

6.3.2.1. Analysis plan

To begin, the results provide a description of how the data was cleaned, including the removal of participants based on specific criteria. Then, how each of the study variables were processed, coded, and converted into scores for the analysis was described. Afterwards, Spearman correlations were conducted between the mental health variables: anxiety, depression, and stress, and the five usage variables: smartphone addiction, daily screen time estimation, daily pickups estimation, average daily screen time, and average daily pickups. Differences in the size of the coefficients which occurred as a consequence of correlating different smartphone use variables with mental health, were then compared to see if these differences were statistically significant. Then, exploratory analysis examined if there were differences in smartphone usage between groups with low and high mental health symptomology, across the five smartphone usage variables. Finally, linear models were developed that aimed to predict mental health symptomology based on various smartphone variables.

6.3.2.2. Data removal

The survey received 263 respondents. However, this became 207 after removing those who did not have iOS12 installed, did not have an iPhone 5 or later, did not have seven days of screen time data on their smartphone, or did not complete the survey or health questions. A further person was removed after being identified as an outlier when plotting data; they reported weight and BMI values more than three standard deviations from the mean. Finally, seven people were removed due to input errors (typos) in their health data. This left 199 participants for analysis.

6.3.2.3. Data coding and processes

Table 6.3. contains the descriptive statistics for all variables. Hours and minutes were reported separately in two different responses when gathering daily smartphone screen time data from the Apple Screen Time settings. To combine and create one screen time variable for each of the seven days, minutes was converted into a decimal as follows: minutes / 60. This decimal was then added to the 'hours' response, to get a complete screen time measure (in hours) for each day. An average daily screen time score was then computed per person by taking the daily amount of screen time from the first six days and then calculating the mean. Six rather than seven days were used to compute this mean, as data from the seventh day did not represent a full day. In a similar manner, an average daily pickups score was calculated per person by taking the daily number of pickups from the first six days and then calculating the mean.

Estimated average daily screen time was also collected in two different responses; one for hours and one for minutes. Matching the calculations conducted for actual screen time, both these responses were combined to create an estimated value (in hours) for the analysis. Raw estimated number of daily pickups were used in the analysis; thus, no manipulation was performed on this data.

The daily physical activity variables; average daily steps and average daily 'walking and running' distance were created by selecting the six days of data which corresponded to the same six days aggregated in the smartphone variables. The daily activity statistics from these six days were then averaged for each measure. If a participant reported their daily 'walking and running' distance in miles, this was converted to kilometres by multiplying the value by 1.60 before creating this average. Furthermore, for the smartphone addiction scale, GAD-7, and PHQ-9, the responses were summed to create a total score for each scale. Specific questions within the perceived stress scale required reverse coding, and then an overall sum was created per person.

Lastly, several processing steps were conducted to calculate BMI per person. To get a total height in centimetres from those who answered using metric units, the 'height in meters' response was multiplied by 100 and then added to the 'height in centimetres' response. Imperial responses were converted to centimetres by multiplying the 'height in feet' response by 30.48, and the 'height in inches' response by 2.54, which were then added together. Then, to get a total weight in kilograms per person, the raw kilogram responses were used from those who chose to answer in metric units. Imperial responses were converted to kilograms by multiplying the 'weight in stones' response by 6.35, and the 'weight in pounds' response by 2.20, which were then added together. Finally, body mass index (BMI) was calculated from these values using the following formula:

$$BMI = Weight(kg) / Height(m)^2$$

6.3.2.4. Effect size analysis

Following study 1, to explore if differences in smartphone measurement influenced the size of the relationships with health, Spearman correlations were conducted between all the health and smartphone variables using Fieller, Hartley & Pearsons (1957) variance when calculating 95% confidence intervals (see Table 6.5.). Spearman correlations were also conducted between all the smartphone measures to document differences between them (see Table 6.4; Fig. 6.2.). Alpha's remain uncorrected for multiple comparisons.

Mirroring study 1, smartphone addiction scores consistently had effect sizes that were at least .36 or larger when correlated with mental health variables. Estimates and objective variables were lower (all $r_s \leq .21$) (see Fig. 6.3; Table 6.5.). This prompted an additional analysis that assessed whether this effect size deviation across measures was statistically significant. To compare differences in the magnitude between the coefficients, this chapter adopted Hittner, May, and Silver's (2003) modification of Dunn and Clark's (1969) *z* test using the r package 'cocor' (Diedenhofen & Musch, 2015). This is suitable for the comparison of coefficients that are calculated from two dependent groups and share a variable in common (Diedenhofen & Musch, 2015). For example, it was possible using this method to compare whether the relationship between smartphone addiction and anxiety ($r_s = .43$) was statistically and significantly larger than the relationship between average daily screen time and anxiety ($r_s = .16$). Zou (2007) confidence intervals were also calculated, which reject the null hypothesis if the interval does not include 0 (Diedenhofen & Musch, 2015; Zou, 2007). Findings showed that when assessing relationships with anxiety, depression, and stress, that associations with smartphone addiction (PSU) were all significantly higher than the associations with estimates and objective logs (all *p*'s <.05) (see Table 6.6). The size of coefficients were not significantly different when using estimates or average daily screen time to determine associations with any mental health metric (all *p*'s >.05). However, there was a significant difference in effect sizes for mental health associations depending on whether an estimated or objective measure of pickups was employed, with correlations running in the opposite direction (all *p*'s <.05) (see Table 6.6 and Fig. 6.3.).

Table 6.3. Study 2 descriptives.

Health Variables	Mean	SD	α	Smartphone Variables	Mean	SD	α
Anxiety	7.35	5.85	.94	Median Daily Screen Time (hrs)	4.62	2.30	.93
Depression	8.01	6.30	.90	Average Daily Pickups	85.76	39.94	.92
Stress	26.57	8.23	.85	Daily Screen Time Estimate (hrs)	4.38	2.15	
Body Mass Index	25.17	5.38	25.17	Daily Pickups Estimate	47.14	39.81	
Average Daily Steps	5238.07	3345.92	.84	Smartphone Addiction Scale	105.80	24.36	.92
Average Daily 'Walking and Running' Distance	3.77	2.67	.83				

Table 6.4. Spearman correlations between all smartphone variables from study 2.

Smartphone Variable	Smartphone Addiction		Screen Time Estimate		Pickups Estimate		Average Daily Screen Time		Average Daily Pickups	
	Spearman r_s	Spearman 95% *CI*	Spearman r_s	Spearman 95% *CI*	Spearman r_s	Spearman 95% *CI*	Spearman r_s	Spearman 95% *CI*	Spearman r_s	Spearman 95% *CI*
Smartphone Addiction			.44***	.32, .55	.05	-.09, .19	.32***	.18, .44	.17*	.03, .31
Screen Time Estimate	.44***	.32, .55			.15*	.01, .29	.57***	.46, .66	.21**	.07, .34
Pickups Estimate	.05	-.10, .19	.15*	.01, .29			.10	-.04, .24	.30***	.16, .42
Average Daily Screen Time	.32***	.18, .44	.57***	.46, .66	.10	-.04, .24			.37***	.24, .49
Average Daily Pickups	.17*	.03, .31	.21**	.07, .34	.30***	.16, .42	.37***	.24, .49		

Notes: * significant at $p < .05$, ** significant at $p < .01$, *** significant at $p < .001$. Alpha's remain uncorrected for multiple comparisons.

Table 6.5. Spearman correlations between smartphone and health variables from study 2.

Health Variable	Smartphone Addiction		Screen Time Estimate		Pickups Estimate		Average Daily Screen Time		Average Daily Pickups	
	Spearman r_s	Spearman 95% *CI*	Spearman r_s	Spearman 95% *CI*	Spearman r_s	Spearman 95% *CI*	Spearman r_s	Spearman 95% *CI*	Spearman r_s	Spearman 95% *CI*
Mental Health										
Anxiety	.43***	0.31, 0.54	.21**	0.07, 0.35	-.08	-0.22, 0.07	.16*	0.01, 0.29	.16*	0.01, 0.29
Depression	.41***	0.28, 0.52	.19**	0.05, 0.32	-.10	-0.24, 0.05	.16*	0.01, 0.29	.17*	0.03, 0.31
Stress	.36***	0.23, 0.48	.21**	0.07, 0.34	-.10	-0.24, 0.04	.15*	0.01, 0.29	.12	-0.02, 0.26
Physical Health										
Body Mass Index	-.07	-0.21, 0.08	.09	-0.06, 0.23	.11	-0.03, 0.25	.16*	0.02, 0.30	.09	-0.5, 0.23
Average Daily Steps	-.16*	-0.30, -0.02	-.07	-0.21, 0.08	.26***	0.12, 0.39	-.07	-0.21, 0.08	.24***	0.10, 0.37
Average Daily 'Walking and Running' Distance	-.14*	-0.28, -0.00	-.07	-0.21, 0.08	.19**	0.05, 0.33	-.09	-0.23, 0.06	.17*	0.02, 0.30

Notes: * significant at $p < .05$, ** significant at $p < .01$, *** significant at $p < .001$. Alpha's remain uncorrected for multiple comparisons.

Table 6.6. Test's comparing differences in the magnitude of the coefficients when predicting mental health from varying smartphone variables. Each row in the table shows the z score when comparing variable 1's effect size with mental health to variable 2's effect size with mental health.

		Anxiety		Depression		Stress	
Variable one	Variable two	*z*	Zou's (2007) *CI*	*z*	Zou's (2007) *CI*	*z*	Zou's (2007) *CI*
Smartphone Addiction	Screen Time Estimate	3.14**	0.08, 0.36	3.11**	0.08, 0.36	2.10*	0.01, 0.29
Smartphone Addiction	Pickups Estimate	5.44***	0.33, 0.68	5.40***	0.33, 0.68	4.82***	0.28, 0.63
Smartphone Addiction	Average Daily Screen Time	3.48***	0.12, 0.42	3.20**	0.10, 0.40	2.65**	0.06, 0.36
Smartphone Addiction	Average Daily Pickups	3.16**	0.10, 0.43	2.80**	0.07, 0.40	2.74**	0.07, 0.41
Screen Time Estimate	Average Daily Screen Time	0.77	-0.08, 0.18	0.46	-0.10, 0.16	0.92	-0.07, 0.19
Pickups Estimate	Average Daily Pickups	-2.86**	-0.40, -0.08	-3.22**	-0.43, -0.11	-2.61**	-0.38, -0.06

Notes: * significant at $p < .05$, ** significant at $p < .01$, *** significant at $p < .001$.

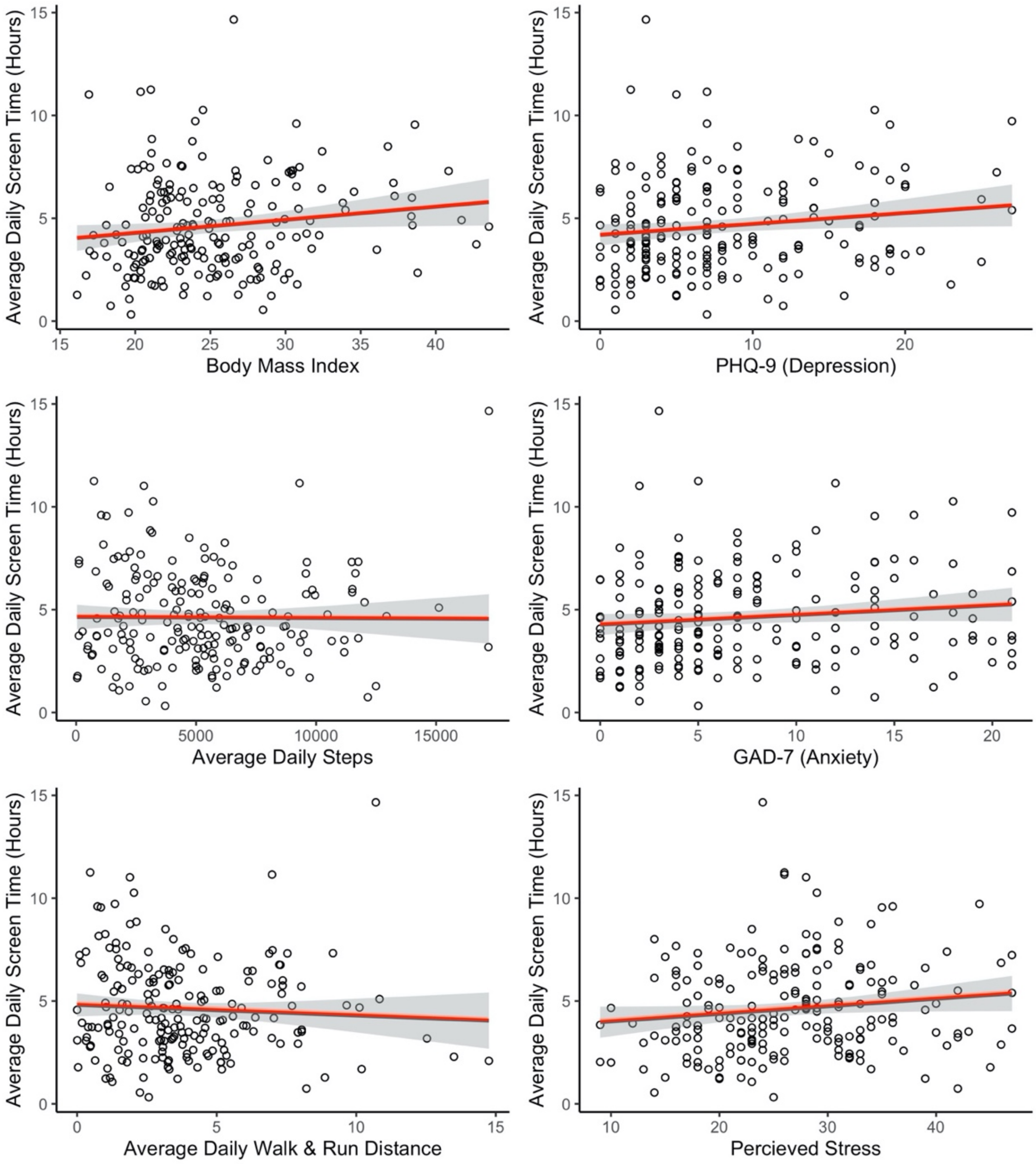

Figure 6.2. Scatter plots of linear associations between average daily screen time (hrs) with six health variables; body mass index, averaged daily steps, average daily 'walking and running' distance, anxiety, depression, and stress. Regression line (red) illustrates linear relationship between each pair with 95% confidence interval (grey).

6.3.2.5. Exploratory analysis – Tests of difference between groups with low and high mental health symptomology.

Measuring 'percentage variance explained' through the exploration of effect sizes has been the subject of some criticism, with some authors advocating that significance testing between groups is a better indicator of whether screen time impacts mental health (e.g., Twenge, 2019). While this approach is in contradiction to many other statistical recommendations (Cumming, 2014), it was of interest to explore whether conclusions would differ if this type of analysis was adopted. Consequently, as the GAD-7 and PHQ-9, have 'cut off points' (≥10) that indicate if people are at risk of having a disorder, this was used to create two groups; 'low risk' and 'high risk'. These measures have high sensitivity and specificity (both > .80) when diagnosing depression and anxiety disorders (Kroenke et al., 2001; 2007). However, due to lack of further psychological assessment, those who exceeded the defined cut-off points for each disorder were considered to be at a higher risk, rather than define an individual as having the disorder. It was then examined if people experienced different levels of daily smartphone use and PSU dependent based on group allocation.

To create groups for the analysis, 50 participants who were considered 'high risk' for both anxiety and depression were collated into one group. This group used their phone for an average of 4.72 hours a day (SD = 2.27) and picked up their phone on average 84.20 times a day (SD = 37.98). Those who didn't exceed the cut-off values for either condition (scored less than 10 on both scales) were placed in a 'low risk' group (n = 124). This group used their phone for an average of 4.41 hours a day (SD = 2.25) and picked up their phone on average 84.07 times a day (SD = 42.55). Wilcoxon rank sum tests showed that the two groups did not significantly differ in their amounts of average daily screen time [$W = 3357$, $p = .39$] or average daily pickups [$W = 3216$, $p = .70$]. This was mirrored when exploring differences in estimated daily screen time [$W = 3489.5$, $p = .19$] and estimated daily pickups [$W = 2721$, $p = .20$]. Therefore, those who were 'high risk' of having both general anxiety disorder and major depression did not use their smartphone's differently to those who were 'low risk' for both conditions. However, a significant difference was found between the two groups on levels of smartphone addiction [$W = 4505.5$, $p < .001$]. Specifically, the 'at risk' group had higher smartphone addiction scores [$M = 116$, $SD = 23.67$] than the 'low risk' group [$M = 98.91$, $SD = 21.91$]. Consequently, if smartphone use is measured with subjective estimates or objective logs, no differences are found between 'high risk' and 'low risk' groups in terms of usage. However, if confounding usage and PSU, one would conclude the opposite if measuring 'usage', via a smartphone addiction scale, incorrectly positing that those with mental health symptomology have higher usage.

6.3.2.6. Exploratory analysis – Linear Regression Models

Many researcher's build predictive models to investigate if there is a linear or logarithmic relationship between health and smartphone usage (Csibi, et al., 2018; David, Roberts, & Christenson, 2018; Kim et al., 2016; Regan et al., 2020; Richardson, Hussain, & Griffiths, 2018). Following suit, linear models were developed that aimed to predict mental health symptomology based on various smartphone variables. Notably, when including all five smartphone measures in models, only smartphone addiction scores significantly predicted mental health scores (see Table 6.7.). Furthermore, models that only contained objective smartphone measures were not significant (all $R^2 \leq .02$, all p's >.05). Finally, average daily pickups significantly predicted average daily steps, and average daily 'walking and running' distance across models (see Table 6.7.).

Table 6.7. Linear regression models with health measures as dependent variables, and smartphone measures as predictors.

	B. with criterion variable						*B. with criterion variable (objective measures of usage only)*					
Model	Anx	Dep	Stress	BMI	Steps	Dist	Anx	Dep	Stress	BMI	Steps	Dist
Intercept	-2.95	-3.65	14.06***	25.05***	6061.84***	4.47***	5.46***	5.55***	24.15***	23.40***	4009.15***	3.35***
Average Daily Screen Time	-0.10	0.04	0.07	0.20	-36.04	-0.13	0.25	0.34	0.45	0.33	-129.31	-0.14
Average Daily Pickups	0.01	0.00	0.00	-0.00	20.20**	0.01*	0.01	0.01	0.00	0.00	21.29***	0.01*
Screen Time Estimate	0.14	-0.03	0.05	0.45*	-44.14	0.07						
Pickups Estimate	-0.01	-0.00	-0.01	0.02	10.01	0.00						
Smartphone Addiction	0.10***	0.11***	0.12***	-0.03	-25.22*	-0.02						
R^2	.18	.17	.13	.06	.10	.05	.02	.02	.02	.02	.06	.03
R^2_{Adj}	.16	.15	.11	.04	.08	.03	.01	.02	.01	.01	.05	.02

Notes: R^2_{Adj} = Adjusted R^2, B = beta estimates, * beta estimates significant to $p < .05$, ** beta estimates significant to $p < .01$, *** beta estimates significant to $p < .001$. Anx = Anxiety, Dep = Depression, Stress = Stress, BMI = Body Mass Index, Steps = Average Daily Steps, Dist = Average Daily 'Walking and Running' Distance, All VIF scores between 1 – 2 and all tolerance scores > .59.

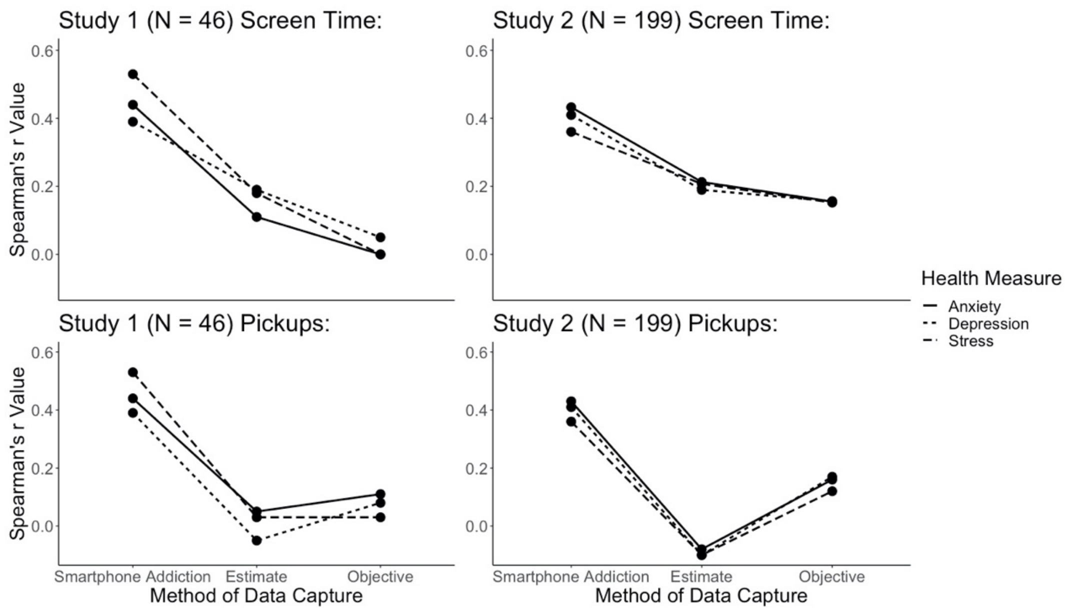

Figure 6.3. Visualising how a change in measurement effects relationships observed between smartphone use and depression, anxiety, or stress across both studies. Top row illustrates how smartphone addiction scores, estimated and actual screen time correlate with mental health. Bottom row replaces estimated and actual screen time with pickups.

6.4. Discussion

This chapter considered if different conceptualisations and measurements pertaining to 'smartphone use', can generate contrasting associations with health. Across two samples including iPhone (*n*=199) and Android (*n*=46) users, it was observed that PSU scales produced larger associations with mental health when compared with subjective estimates or objective logs. Notably, the size of the relationship was fourfold in study 1, and almost three times as large in study 2. Specifically, $r_s \leq .17$ were repeatedly found between objective smartphone use (daily pickups and screen time) and mental health symptomology (anxiety, depression, and stress), whereas larger effect sizes were observed when relying on a problematic usage scale (all $r_s \geq .36$). This was further supported with statistical models, which demonstrated that average daily pickups and average daily screen time did not significantly predict anxiety, depression, or stress, and explained less than 2% of the variance. Additionally, those who exceeded the clinical 'cut off points' for both general anxiety and major depressive disorder did not use their phone significantly more than those who scored below a standard threshold. Finally, in terms of physical health, while previous research has observed assocations between higher smartphone addiction scores and lower muscle mass (Kim, Kim, & Jee, 2015), our findings derived from objective logs are less clear-cut.

However, generally speaking, conflating an individual's appraisal of their smartphone use with actual usage generates vastly different relationships with well-being. This is problematic given a recent review confirmed that 70% of studies in this area adopt PSU scales (Thomee, 2018). The same review also concluded that intense or frequent mobile use was associated with greater mental health symptomology, yet this conclusion was based primairly on findings derived from PSU scales. Findings from this chapter would alternatively suggest that helping people manage appraisals of use (e.g., worries) is more likely to benefit wellbeing than reducing use of the device itself. Consequently, one might question whether reducing actual smartphone use should be a priority for any intervention development at this time.

Recent research has arrived at broadly similar conclusions. For example, ‘intense’ general smartphone use did not predict negative wellbeing from objective logs (Katevas, Arapakis, & Pielot, 2018). Another study that measured objective smartphone screen time over a weeklong period, observed that average daily depressive mood positively correlated with smartphone addiction scores, yet objective screen time minutes were not related to depression and anxiety (Rozgonjuk et al. 2018). In terms of studies that rely on duration estimates, large-scale designs that follow Open Science practices have also reported small effect sizes. For instance, in a large sample of New Zealand adults (n = 19,075), associations between social media use and wellbeing was found to be weak (Stronge et al., 2019). When using specification curve analysis to examine self-reports from a large sample of adolescents (n = 355,358), the association between digital technology use and wellbeing was found to be small, explaining only 0.4% of the variance (Orben & Przybylski, 2019). In our sample, objective screen time and pickups explain less than 2% of the variance in mental health.

Placing our findings in a broader context, the relationship between objective use and mental health (all $r_s \leq .17$) is lower than the average effect size found across many psychology studies (r = .21), just slightly less than the relationship between Nicotine patch (vs. placebo) and smoking abstinence (r = .18), and about the same size as the relationship between post-high school grades and job performance (r = .16) (Funder & Ozer, 2019; Meyer et al., 2001). When adjusting for new recommendations that 'small', 'typical', and 'relatively large' effects fall around r coefficients of ~.10, ~.20 and ~.30, respectively (Gignac & Szodorai, 2016), the suggestion that social media has, for example, *"destroyed our lives"* (Appel, Marker, & Gnambs, 2020, pp.62) would warrant medium to large effects (r >.20). Using this benchmark, our findings would suggest general smartphone use does not have extreme or profound effects on wellbeing, contrary to repeated claims suggesting otherwise (e.g., Twenge, 2017). At the same time, very large effects of $r \geq .40$ in psychology studies are likely to overestimate a genuine effect and, as a result, warrant additional scepticism (Funder & Ozer, 2019). For example, the relationship between anxiety and smartphone addiction in study 2 was equivalent to the relationship between height and weight (both r_s = .43).

Scores from PSU scales may generate larger associations with mental health for several reasons. First, one could argue that negative appraisals of smartphone use (or technology use more generally) is based around issues that pertain to the regulation of everyday behaviour. Specifically, while people would like to perhaps regulate technology usage as they would with any other everyday behaviour, this is not always possible and this discrepancy between actual and desired use can lead to negative or positive appraisals (O'Connor and Rosenblood, 1996; Stich, et al., 2019). Second, both overall scores derived from the SAS and individual items have latent relationships with stress and depression scales (but not with objective smartphone measures) (Davidson, Shaw, & Ellis, 2020). Hence, cross-loadings between PSU and mental health could artificially inflate relationships due to a lack of independence. Third, 'method bias' may be influencing the size of the correlation coefficients due to linguistic similarities between items across mental health and PSU scales (Podsakoff, MacKenzie, & Podsakoff, 2012). Every question in the SAS (and the majority of related scales) assesses a percieved problem, echoing mental health scales (Kwon et al. 2013; Spitzer, et al., 2006; Kroenke, et al., 2001). However, this negative wording could be a further source of bias. For example, it has been shown that correlations between role conflict, role ambiguity and other constructs reduced by 238% when controlling for wording effects, by balancing the number of positively and negatively slanted questions (Harris & Bladen, 1994; Podsakoff, MacKenzie, & Podsakoff, 2012).

6.4.1. Future Research

Future research that aims to specifically consider the impact of smartphone *use* should, where possible, adopt a more nuanced approach to understand both the costs and benefits of specific smartphone applications (as outlined in chapter two) that can be monitored remotely (Geyer, et al., 2020). Recent work has shown that while total time spent using smartphones had $r = .16$ effect sizes with anxiety and depression, certain categories of applications has more beneficial relationships (e.g., time spent reading books) (David et al., 2018). Therefore, claiming general smartphone use as negative or positive oversimplifies a very complex and multifaceted phenomenon. For example, the relationships observed between body mass index and objective smartphone use were incoherent across our two studies. However, there appears to be a positive relationship between average daily steps and average daily 'walking and running' distance with objective daily pickups. These results further question whether all smartphone behaviours should be considered sedentary when deliberating the relationship between usage and physical activity. Arora et al., (2013) found that computer use, tv viewing, and video gaming were associated with increased BMI, but conversely, did not find the same for mobile phone use. They stated, *"the portable nature of a mobile telephone does not require the user to remain in one place during use, thus allowing movement"* (Arora, et al. 2013, pp. 1258). In line with recent discussions, screen time is often conceptualised in absence of 'exergaming' and other activities which involve physical activity whilst engaging with the device (Kaye, et al., 2020).

It remains difficult to objectively measure the use of a specific application across many devices (e.g., documenting time spent on Netflix across smartphones, televisions, and tablets) (Kaye et al., 2020), and in these cases, researchers may still have to rely on estimates of use. However, findings from this chapter continue to confirm the consistent discrepancies between objective logs and subjective estimates (see Table 6.4.) (see chapter four; Andrews et al., 2015; Boase & Ling, 2013; Parslow, Hepworth, & McKinney, 2003; Ellis et al., 2019; Kobayashi & Boase, 2012; Lee, et al., 2017; Vrijheid et al., 2006). In study 2, and as observed previously (see chapter four), estimated frequency of 'pickups' had greater deviation from its objective counterpart than screen time estimates. Thus, if subjective estimates are to be collected, it is advised that researchers start including this measurement error into statistical models, which has now been quantified (Ellis, 2020; van Smeden, Lash and Groenwold, 2019).

6.4.2. Limitations

Both studies were cross-sectional; therefore, it is not possible to make any causal claims regarding the impact of smartphone use and mental health. However, by using a quasi-experimental approach in the exploratory analysis of study 2 and through analysing the naturally occurring levels of mental health symptomology, the findings cast doubt on the presence of any causal relationships that have been proposed previously, as those in a high symptomology group did not have increased general smartphone usage. It is further possible that participants may have received feedback from Apple Screen Time prior to the study, which would have influenced their estimation of use. The size of the relationship between estimated screen time and actual screen time is larger in study 2 than previous work and may explain why association between mental health and these two measures of usage did not significantly differ (Andrews, et al., 2015; Ellis, et al., 2019). However, this does not mitigate the need to control for errors between actual and self-reported screen as part of any future analysis.

In addition, by moving the second study to an online platform, a larger and more representative sample was achieved. However, this meant losing some of the precision obtained with laboratory based bioimpedance measures when examining physical health. Nonetheless, as BMI scores in study 1 had large correlations with body fat percentage (r_s = .70) and skeletal muscle mass % (r_s = -.73), this was accepted as a relatively good proxy in study 2. Furthermore, as self-reports of height and weight may also have measurement error, the ranges of BMI values were analysed. The sample in Study 2 specifically had BMI values that were in line with what might be expected in representative sample (WHO, 2018). However, future research would benefit by exploring how body composition (including body fat percentage) could be collected objectively when relying on remote data collection.

6.4.3. Conclusions

To conclude, choosing between measurement tools, and accepting the benefits and limitations of that choice is an unavoidable facet of all research. However, when understanding or making claims regarding the effects of a particular behaviour on health, the cost of any error can be considerable. Chapter six demonstrates that problematic smartphone usage scales have significantly larger relationships with mental health when contrasted with objective logs of use. These are nearly thrice in a large sample and fourfold in a small sample. Thus, if a research question concerns technology usage, then objectivity should remain the preferred measure. The notion of ‘problematic use’ requires stringent examination because it is frequently conflated with behaviour, despite a general acceptance that ‘excessive’ smartphone usage does not neccesaily equate to ‘problematic use’ (Billieux, Philippot, et al., 2015; Panova & Carbonell, 2018). Consequently, PSU scales may only capture people’s appraisals of their smartphone use, rather than an underlying pathology or behaviour. Finally, the findings from chapter six would favour addressing peoples’ appraisals about their usage rather than reducing their overall screen time, as the former relates more strongly to mental health. Even if specific worries in relation to mobile technology are widespread, limiting general smartphone use or engaging with any form of ‘digital detox’ is unlikely to have any demonstrable benefits and should not be a priority for public health interventions at this time (Wilcockson, Osborne & Ellis, 2019)

Chapter 7

General Discussion

7.1. Thesis Overview

7.1.1. Thesis Objectives

The main research question of this thesis was, *"Can a person's mobile technology use be indicative of a person's individual differences such as personality, demographics and health.* However, before measuring this directly, work was required to set up the theoretical (chapter two), ethical (chapter three) and methodological (chapter four) underpinnings in order to explore this research question with integrity. Consequently, the first objective of this thesis was to explore how studies of technology use could incorporate the collection of smartphone digital traces in their methodologies and was investigated specifically in chapter four. Secondly, this thesis aimed to shift the narrative of solely studying smartphone use with a pathological lens. Therefore, in chapter two, a theory describing 'everyday' and 'common' smartphone use was proposed, and findings from chapter six challenged existing positions which considered increased smartphone use as problematic. Finally, to address the third objective of this thesis, chapters five and six sought to understand whether objective smartphone use could predict a user's personality, demographics, and health. Chapter seven brings this thesis to a close, by providing a final overview of the contributions made by each chapter as a collective, to discuss challenges and future directions when ascertaining individual differences from digital traces of behaviour.

7.1.2. Chapter Summaries

The introduction of this thesis outlined how the ever-growing universe of digital data affords new opportunities to study the influence of technological advancements, such as the advent of smartphones on people and society. In particular, it described how smartphones play an important role in the creation if this digital data, given they are "always on, and always on you" (Turkle, 2008, pp. 121). Descriptive statistics from chapters four, five and six would support this idea of human-smartphone tethering, as people spend on average between 3.71 – 4.78 hours a day on their smartphone and pick up their phone on average between 88.91 and 133.18 times a day. Consequently, a person's smartphone use equates to a large proportion of their everyday behaviours and has great potential when revealing information about their unique characteristics.

Given these norms, it can be posited that using the device for several hours a day may not necessarily be pathological. Yet prior to chapter 2, psychology was still to propose a theoretical understanding of non-pathological technology use, which has great pertinence given it encapsulates a quarter of all waking behaviours. The Technological Integration Model (TIM) therefore, provided a theoretical route forward by describing the predecessors behind usage behaviours and through conceptually describing how people amalgamate with the technology they own. By redefining the principles of extended self with relevance to technology use, it becomes theoretically plausible that user characteristics can be obtained through analysing a person's digital usage patterns.

Historically, a researcher may collect numerous smartphone traces when making personality predictions, such as battery levels, screen state, call logs etc. as even a small percentage increase in accuracy from any one of these variables is given high value (Montag et al., 2019; Yarkoni & Westfall, 2017). However, there is a trade-off between increased measures and user privacy. Chapter three addressed this issue by exploring whether the most basic meta-data that can be collected on a person's device, the smartphone operating system (iPhone/Android), provides enough personalisation to be indicative of the user's individual differences. Findings showed that four variables in particular were able to predict smartphone ownership reliably across two samples with 69% accuracy. These were gender, phone as status object, honesty-humility, and avoidance of similarity. Pertinently, the last two variables alone could predict ownership with 67.29% accuracy when building conditional inference trees. Consequently, as predicted by the technology integration model, the choice to use a particular technology can be indicative of a person's characteristics.

Additionally, chapter three showed that algorithms trained on participant responses have the potential to outperform observer ratings of personality, as study 3.2. revealed that stereotypes regarding iPhone and Android users did not always align with the actual traits scores found in study 3.1. Hence, the smartphone operating system a person uses can achieve reliable personality predictions when using machine learning techniques. This is not an invasive digital trace to collect when compared to alternatives such as call logs. The ethical implications of this are discussed later in this chapter, but importantly, the remaining studies of this thesis followed suit by studying only basic digital traces. Where possible, this thesis also collected data on both Android and iPhone users, as a result of the differences described above. This has large implications for research in Psychoinformatics (Yarkoni, 2012), given that the type of digital traces that can be extracted from iPhone and Android devices can vary in type and resolution.

Chapter four then explored how another simple digital trace, a person's smartphone screen time, could be obtained from both iPhone and Android phones. The purpose of this was to investigate smartphone data acquisition, alongside the validity of other popular methodologies such as self-reported estimates of use and psychometric scales. In study 4.1., Apple's in-built screen time measure was able to adequately collect day-to-day usage statistics regarding the number of smartphone pickups and screen time hours for the past six days. When compared to self-reports, neither psychometric scales nor estimates were shown to be an adequate proxy for objective logs due to the lack of large effect sizes between the two ($r > .7$). However, asking participants to provide an estimate of their daily pickups and screen time had a stronger relationship with actual usage than any psychometric scale.

Following suit, study 4.2. compared subjective estimates of usage to second-by-second smartphone logs on Android phones across a two-week period. In comparison to 'Apple Screen Time' measures, this higher resolution data made people's rapid checking behaviours visible, as 42.50% of all phone uses were less than 15 seconds in duration. Through analysing the peaks of use, any session which lasted less than 15 seconds in duration were defined as a smartphone check. When compared to self-reports, small relationships were found between estimates and actual checking behaviours. Also, in line with study 4.1. only medium correlations were found between daily estimated and actual screen time.

Collectively, both studies in chapter four bring into question the validity of conclusions in prior research which has used self-report methods of technology use, highlighting the pertinence of this when studying the relationships between health and technology. This inspired the subject matter of chapter six, which explored how the choice of measurement when assessing smartphone ‘use’ can impact the relationship between health and technology use. Hence, chapter four provided the methodological direction of the remaining chapters of the thesis, not only in relation to the use of objective measures, but also when understanding the length of time researchers should monitor people’s usage patterns for. Specifically, findings from study 4.2. showed that five days of data was needed when examining screen time, but only two days for checks and pickups in order for this to be representative of their normal usage behaviours.

By chapter five, this thesis had established both theoretical and methodological grounding, alongside an understanding that even simple digital traces could reveal information about a person’s individual differences. Chapter five then addressed the main research question by studying whether objective smartphone usage patterns could predict a person’s age, gender and HEXACO traits. The results of chapter five showed that digital traces of smartphone usage data could be informative of a person’s demographics and also revealed a person’s unique ‘smartphone usage personality’ when adopting an ideographic approach, but against predictions, was not informative of broad personality traits. Likewise, chapter six showed across two studies, containing both iPhone and Android user’s that objective smartphone use is a poor predictor of a variety of health outcomes. However, when using problematic usage scales to study the relationships between smartphone use and mental health, stronger relationships were found. The next part of this chapter describes these findings in greater detail to explain how they address the three objectives and the overarching research question outlined in the beginning of this thesis.

7.2. Theoretical Considerations

The central research question throughout this thesis was *"Can a person's mobile technology use be indicative of a person's individual differences such as personality, demographics and health?"*. This can be broken into three parts, analysing the relationships with personality, demographics, and health separately.

7.2.1. "Can a person's mobile technology use be indicative of a person's personality?"

Belk's extension-of-self theory (Belk, 1988, 2013) and the Technology Integration Model (TIM; see chapter two) hypothesised that a person's individual differences such as personality could be predicted from the way a person uses their technology. In particular, TIM and extension-of-self theory describe how technology can extend a person's mind, as whenever a person uses a technology, the choices and personalisation they make (e.g., deciding what music to play on Spotify) extends their characteristics into their technology use patterns. Furthermore, TIM and extension-of-self theory describe how greater agency over technology provides greater opportunity for personalisation, and thus, greater self-extension (Belk, 1988, 2013). Therefore, TIM predicted that digital traces with greater variability (e.g., application usage behaviours vs operating system choice) would lead to better personality predictions.

Chapter three found that one broad trait in particular, honesty-humility from the HEXACO framework (Lee & Ashton, 2004), was predictive of the smartphone operating system a person chose to use. Specifically, binary logistic regression modelling showed that the inclusion of honesty-humility scores in a model significantly improved its Chi-square statistic. Furthermore, in random forest modelling, honesty-humility was in the top four most important variables when assessing which contributed the most to the accuracy of the model. However, none of the other five HEXACO traits contributed to smartphone ownership predictions. Similarly, in chapter five, none of the HEXACO traits reliably correlated with daily hours of use, pickups, checks, and many other smartphone variables which included the usage of 29 popular applications. Therefore, chapter five rejected the hypothesis that smartphone usage variables would predict HEXACO personality traits.

It has been observed in previous research that some personality traits can be better predicted from certain digital traces than others (Montag & Elhai, 2019). This may explain the lack of relationships described above. For example, extraversion might be related to more specific behaviours within communication applications. This has been shown in a recent article whereby extraversion was positively related to a person's frequency of Facebook status updates, collected objectively via Facebook's API (Marengo, Poletti, & Settanni, 2020). A person with high extraversion is described as someone who "enjoys social gatherings and interactions" (see hexaco.org). Thus, it is possible that the frequency of Facebook status updates is a more direct way of measuring the trait extraversion, than general use of social media applications, which was explored in chapter five. Consequently, it is possible that more general smartphone use variables lack the nuances to capture behaviours which would be specific to the people who embody greater amounts of each trait.

However, honesty-humility in chapter three was found to predict smartphone operating system ownership. This trait describes a person's interest in lavish wealth, luxuries, and social status (see hexaco.org). It is possible that honesty-humility may have had particular relevance to the ownership of iPhone's due to their promoted social status in advertisements *"If it's not an iPhone, it's not an iPhone"* (Miller, 2015). Furthermore, people often described finances in study 3.2. as a factor which differentiates iPhone and Android users. Hence, this digital trace can be said to directly measure the description of the honesty-humility personality trait, explaining why relationships were found. Accordingly, when assessing the ability to predict personality from digital traces, a researcher must be able to theoretically explain why that link would exist, with the expectation that more direct measures of that trait would outperform those with looser connections. This rationalises why certain digital traces are better predictors of a particular trait than others and is not necessarily related to the generality of the digital trace, but more so the relevance (Montag & Elhai, 2019).

The reverse is also an issue, whereby the more abstract a personality trait is, the more imprecise a personality measure will be at predicting a particular behaviour (Alison, Bennell, Mokros, & Ormerod, 2002). Known as the 'abstraction issue', this would explain why in chapter three, measures that were more conceptually related to smartphone operating system choice, namely, avoidance of similarity (when choosing products), and the perception of your phone being a status object, had stronger relationships with operating system choice than more general personality traits (Alison et al., 2002). Interestingly, this observation has wider implications. Take for example the use of a personality test when assessing the suitability of job candidates. Findings here would suggest that examining traits which are more specific to workplace behaviours (e.g., ‘organizer’) (Mathieu, et al. 2015), would be better predictors of that candidate’s future workplace behaviours than broad personality traits. Therefore, digital traces of behaviour might be more predictive of personality traits if the measured characteristics are less far removed from the technology use itself.

This highlights a well-known limitation of broad-trait approaches; they often do not predict a person’s behaviour accurately across all situations (Mischel, Shoda, & Ayduk, 2008). However, it is important to comment that this was never the original intention of trait-based approaches. Gordon Allport (1962) described how the variability in behaviour makes it difficult to predict how a person will behave in a very specific situation. However, amongst this variability there is a level of underlying consistency in people’s behaviour, and personality traits seek to explain this portion of behaviour (Allport, 1962). In correlational research, this would manifest in effect sizes that only explain a certain proportion of the variance in people’s behaviours. Coined the ‘personality coefficient’, researchers have claimed that the relationship between self-reports of personality and measures of behaviour have an upper limit, which ranges between $r = .2$ and $r = .4$, and would equate to explaining at most 16% of the variance in behaviour (Funder, 2009; Maltby, Day, & Macaskill, 2010). Therefore, if researchers aim to make personality predictions from digital traces, it is advised that a project should bear in mind the personality coefficient when determining sample size in power analysis.

Consequently, it is also possible that given a larger sample size in study 5.1, that some of the smaller relationships would have reached significance. Whilst the sample size in study 5.1. mirrored prior research, which correlated personality scores to objective phone usage (Montag et al., 2014), power analysis showed the study was only able to explore medium-to-large effect sizes (r > .4), which is the upper limit of the personality coefficient. Depending on the purpose of the study, a researcher may be interested in these effect sizes. However, if the purpose of the project is to see whether digital traces could be used as a substitute for traditional personality tests, then larger relationships would be required. Given all the points above, it can be questioned whether alternative approaches to personality assessment beyond traditional trait perspectives would provide a more fruitful route forward when inferring characteristics from digital traces.

One such approach is interactionalism, which states that a person's behaviours cannot be understood from either personal or situational factors alone, and instead should be examined together using a dynamic method (Mischel, 2004). Specifically, *"interactionalism focuses on how the expressions of the stable personality system are visible in the person's unique patterns of if…then... situation-behaviour relationships"* (Mischel, Shoda & Ayduk, 2008, pp.88). The second half of chapter five adopted this approach by measuring whether an individual's behaviour was consistent when using the same applications but diverged between applications. This was achieved by creating standardised behavioural profiles of people's daily application use, separately for the variables; daily application pickups, daily application checks and daily application time. Within these, fluctuations in individuals' behaviours were visible across different applications (e.g., a person uses Instagram for an hour a day, but the camera application for only five minutes). However, the way in which people's behaviour varied across the applications was actually quite stable across days (e.g., always used Instagram the most). Notably, random forest models trained on six days of daily behavioural profiles could classify users from an anonymous seventh day profile with 99% accuracy, and this was the case for all variables measured. Therefore, interactionalism offers a promising approach when predicting future behaviour from digital traces and can also map the unique characteristics of a particular individual.

On the other hand, it can be said that the interactionalist approach lacks generalisability, as the predictions made are specific to an individual in question. However, one could easily turn this into a nomothetic endeavour by aggregating scores across all situations, thus treating situations as a sort of 'noise' not dissimilar to existing trait approaches (Mischel et al., 2008). Specifically, say a person wanted to generate scores for the characteristic 'application user'. All that is required is the calculation of average usage across all applications, thus 'averaging out' the influence of the situation. This score could then be used like any other trait score to see how this relates to a variety of behavioural and psychological outcomes. Arguably, creating 'broad traits' in this manner can reduce the level of abstraction if wanting to make more accurate behavioural predictions from trait-based approaches.

Furthermore, prior to the development of smartphone data collection applications, one of the barriers to interactionalism was the effort required to measure a person's actual behaviours across several situations (Mischel, 2004). However, chapter five has highlighted that the Psychoinformatics approach is in a unique position to address this, given the possibilities of new smartphone methodologies. For example, the *if…then…* functions proposed by Mischel & Shoda, (1995) could be assessed by examining *if* GPS location equals x, *then* the specific behaviour elicited is y (e.g., *if* in a coffee shop, *then* a person uses apple pay/ reads the news/ checks emails) (Montag & Elhai, 2019).

The wealth of sensors that reside in smartphones such as WIFI, GPS, NFC, cellular network, digital camera, light sensors, accelerometer, phone status logs, application usage logs, SMS logs and call logs (Piwek & Joinson, 2017), provide endless opportunities to examine *if…then…* relationships. This could also be paired with ecological momentary assessment, if wanting to gather user self-reports (Trull & Ebner-Priemer, 2014) and can be sent to an individual's smartphone directly using customised applications (Montag et al., 2019).

Moreover, by adopting computational approaches, decision tree algorithms could also be used to visualise a particular person's *if…then…* relationships. This is because decision tree algorithms produce rules (e.g., *if* women, *then* classify as iPhone owner). This would be entirely possible if a person's behaviour is collected across several situations multiple times and would be a contemporary way to create and visualise behavioural profiles. The 'stability' of a person's trees could also be assessed by testing the accuracy of the model on unseen data, or through the use of newly proposed metrics (Jacobucci, 2018). Thus, whilst the interactionalist approach was proposed five decades ago (Mischel, 1973), new data sources and computational power described in the Psychoinformatics approach afford novel opportunities to investigate person-situation interactions (Montag & Elhai, 2019).

Interactionalism can be said to fall under the umbrella of ideographic personality research, which aims to obtain a rich understanding of the dynamic dispositions of the individual (Maltby et al., 2010). However, by collecting detailed logs of people's digital traces, it is also possible to conduct exploratory and descriptive research. Specifically, this thesis found across chapters four and five that sample wide smartphone checking behaviours followed a pattern when plotting the frequency of uses which lasted specific durations. Distinct peaks of use occurred at two seconds, six seconds, and eleven seconds across both chapters. When doing subject specific analysis, the shape of these checking histograms was found to be unique to the individual, but consistent across their day-to-day use. Notably in chapter five, random forest models trained on six days of checking histograms could classify users from an anonymous seventh day checking histogram with 59% accuracy. Thus, by conducting exploratory research, it is possible to develop novel personality variables that have not previously been considered, that are driven from the data itself. These are divorced from existing taxonomies of traits altogether and can address the limitation that taxonomies such as the 'Big 5' can be considered restrictive because they limit individual differences to only a handful of dimensions (Hinds & Joinson, 2019). Thus, there is promise in understanding how digital traces relate to a person's characteristic when adopting data driven and ideographic approaches, which is largely obsolete in current research.

Consequently, when answering the research question *"Can a person's mobile technology use be indicative of a person's personality?",* this thesis would argue yes, given the following conditions. If using existing personality taxonomy's such as the 'Big 5', there needs to be a plausible link between the digital trace being measured and the proposed trait, with the expectation that relationships would exhibit small to medium effect sizes at best. Traits which are more specific to the digital trace being measured are likely to show stronger relationships than those less relevant. Thus, it is not an effective approach to measure all the possible digital traces that can be obtained from a device at once, without any psychological intuition. Furthermore, ideographic approaches can produce accurate predictions regarding future behaviour's by studying the unique characteristics of people's digital traces and can even reveal new types of individual differences. Therefore, in line with the Technology Integration Model, people's unique personalities can be derived from studying their technology usage patterns, when following the appropriate methodologies. Specifically, when adopting an ideographic approach, digital traces that allow for more personalisation (e.g., application use), produce more accurate predictions than those with less variation (e.g., checking behaviours), in line with the assumptions made by the Technology Integration Model. However, when following a nomothetic approach, trait-to-trace relevance has greater importance than the customisation potential of the behaviour measured in the digital trace.

7.2.2. "Can a person's mobile technology use be indicative of a person's demographics?"

Individual differences are described in the Technology Integration Model as a precursor of technology use (see chapter two). This includes demographics such as age, gender, and social economic status. Specifically, the model describes how individual differences effect the way a technology extends and subtracts from a user and will influence whether it's considered worth using or not. Furthermore, TIM describes how individual differences may influence the motivations towards using a technology. Consequently, it was predicted throughout this thesis that demographics could be inferred from the resultant technology usage patterns.

In support of TIM, findings from chapter's three and five showed that age and gender in particular can be discerned from digital traces of behaviour. Meta data such as the device a person is using can infer gender, as women were twice as likely to own an iPhone than Android phone (OR = 2.27) in chapter three. Decision tree models also showed that gender was important when making predictions regarding smartphone operating system ownership. If a participant's 'phone as status object' score was less than 2.5, then classification depended on their gender: men were classified as Android users and women were classified as iPhone users. Chapter five also showed that daily application use differed between men and women. Therefore, digital traces of technology use have the ability to infer a person's gender from their usage patterns and device ownership.

This is in line with earlier research which has shown gender can be predicted from technology use. Notably, chapter five replicated a previous study which showed that men spent longer on the Google Play Store than women (OFCOM, 2018). In addition, gender has previously been shown to predict the use of social, e-commerce, productivity, sport, and other mobile applications (Kim, Briley, & Ocepek, 2015; Quin et al., 2018; Stachl et al., 2017). When shopping for a new device, men gravitate towards the technical aspects of mobile phones such as operating system, battery life, screen size and processor speed in comparison to women who pay greater attention to price, service contract terms and camera capabilities (Nielsen, 2014). Therefore, it is likely that men and women have different drivers and motivations behind smartphone use which is reflective in their choice of applications and device use, as predicted by the Technology Integration Model.

Similarly, ‘age’ in chapter three was shown to be the second most important variable when predicting smartphone ownership across many decision trees during random forest modelling. Also, in chapter five, there was an overall trend across several variables; as age increased, general smartphone use decreased. Notably, the length of inactivity between phone uses had a large positive relationship with age. Therefore, digital traces of technology use have the ability to also infer a person’s age from device usage choices and patterns.

It is possible that as age increases, people’s routines naturally gravitate towards reduced screen time and longer time intervals between uses. Findings here alongside previous research would suggest this is the case. In a cross-sectional sample of older adults, a survey showed that ICT use decreases with age (Vorrink et al., 2017). In a similar survey of 7609 individuals, higher prevalence of technology use was associated with younger age and being male (Gell, et al., 2015). A younger demographic is also related to increased smartphone use when measuring screen time (Christensen et al., 2016). Therefore, in line with the Technology Integration Model, it might also be possible that people’s motivations towards using their smartphone and the goals they wish to achieve via use may change with age. By conducting within-subject longitudinal research, it would be possible to test the hypothesis that technology use reduces over a person’s lifetime.

The ability to predict demographics from digital traces of smartphone use could be used in future to conduct mass population screening, without the cost and effort that is normally associated with postal or telephone surveys. For example, once in a decade, the U.K. conducts a country wide postal survey called the census which collects demographic information to get a detailed snapshot of society (Office-for-National-Statistics, n.d.). The purpose of this is to inform government and local authorities of places which need additional services such as education establishments, doctor's surgeries, libraries and roads etc. (Office-for-National-Statistics, n.d.). However, the survey also informs businesses of prime locations to build new stores, provides a historical account of U.K. regions, and can be used by voluntary organisations to learn about the communities they operate in (Office-for-National-Statistics, n.d.).

Findings from this thesis suggest that national surveys such as the census could move to a more digital platform, by creating a smartphone application, whereby a collection of digital traces alongside self-report questions could provide rich information about society. GPS logs could examine which roads are most used alongside people's home and work locations. Age and gender can be inferred from smartphone usage patterns (see chapters three and five). Furthermore, it has also been shown that employment status, ethnicity, education and income can be inferred from smartphone traces too (Christensen et al., 2016; Kim et al., 2015; Rivron, Khan, Charneau, & Chrisment, 2016). A person's installed smartphone applications alone have been shown to predict a person's religion, relationship status and whether they are a parent, through detecting the installation of children or dating applications (Seneviratne, et al., 2014). The only effort required by participants would be the downloading of a smartphone application, which could automatically measure these traces. Consequently, this has the potential to assess a wider proportion of the population, on a more regular basis, without the need for people to fill in and return a survey via post.

Predicting people's demographics from smartphone use is also important during criminal investigations. Specifically, the field of 'mobile forensics' is the practice of recovering digital evidence from mobile devices (Asim et al., 2019). Chapter's three and five show it is possible to profile the age and gender of a particular device owner via an examination of past usage. This is particularly beneficial given that usage logs can now be retrieved retrospectively using newly designed software (Geyer, et al. 2020). These two demographic factors, alongside the postcode of a person's home (which can be analysed via past GPS locations) could be inputted into police databases to identify a user. Furthermore, behavioural science labs are starting to investigate whether characteristics retrieved from digital 'social signals' can be used during crime prevention by assessing risk (CREST, 2020). Therefore, as a final note, the ability to infer demographics from digital traces has useful security applications. This includes profiling a person of interest across devices (i.e. personal v's burner phone) or using these 'digital biometrics' to approve the access of sensitive or age restricted information.

7.2.3. "Can a person's mobile technology use be indicative of a person's health?"

Another ambitious line of research which is being explored in recent times is the ability to infer people's mental health from digital traces of behaviour. This has included estimating stress levels, overall mood, happiness, social anxiety, subjective wellbeing, loneliness and depression from smartphone sensors and usage logs (Bogomolov, Lepri, & Pianesi, 2013; Gao, Li, Zhu, Liu, & Liu, 2016; Gao, Li, & Zhu, 2014; Likamwa, Liu, Lane, & Zhong, 2013; Saeb, Lattie, Schueller, Kording, & Mohr, 2016; Yamamoto et al., 2018). The purpose of this is to avoid participant effort when gathering self-reports regarding a person's mental health, and to allow for continuous evaluation over time (Gao et al., 2014; Yamamoto et al., 2018). Other's state smartphones could provide early detection of mood disorders (Saeb et al., 2016). Therefore, it was explored in chapter six whether smartphone screen time was related to a variety of physical and mental health complaints.

Overall, only small positive correlations were found in study 6.2. between mental health and increased objective screen time and pickups (all *r's* < .17), and in regression models, objective measures explained less than 2% of the variance in mental health. Thus, it is likely that additional or alternative digital traces are required to make better predictions, such as measuring GPS logs to predict depression (Saeb et al., 2016). It is also possible that screen time might be more reflective of momentary wellbeing. However, recent evidence has shown that momentary wellbeing is not related to the use of social applications (Johannes et al., 2020). Nonetheless, these findings have implications for those seeking to understand the effects of smartphone use on health. The small relationships between screen time and mental health symptomology suggest it is unlikely that tools such as 'Apple Screen Time' and Google's Digital Wellbeing application, would have any notable effects on people's mental health, if placing limits on their overall daily screen time.

This was further supported in chapter three whereby increased smartphone use did not strongly relate to smartphone addiction, refuting the notion of tolerance in technology addictions (Griffiths, 2005). This is in line with prior research which showed that people with self-reported internet gaming disorder did not feel the need to increase their time spent gaming (King, Herd, & Delfabbro, 2017), and supports the idea that tolerance does not apply to non-substance ingesting behaviours (Starcevic, 2016). This draws into question the usefulness of applying the addiction framework to technology use if research is unable to support such definitions. Whilst initially developed to understand excessive and problematic use, research is no closer to understanding how addiction impacts technology use, due to the large disagreements between researchers (Ryding & Kaye, 2018).

Moving forward, what can replace the addiction framework when conceptualising technology use? This thesis showed that people spend on average between 3.71 – 4.78 hours a day on their smartphone, and this does not appear to have adverse health consequences. Others have noted that in a relatively short space of time, human-computer interaction has simply become a cornerstone of everyday life (Thompson & Thompson, 2017; Widdicks, Ringenson, Pargman, Kuppusamy, & Lago, 2018). As more amenities are made digital, a growing number of people rely on their smartphone to bank, gather information, manage utilities, seek entertainment and make new friends. Therefore, one could argue that any form of digital dependency is a component of everyday obligations. As chapter one and two of this thesis describes, people are no longer 'independent organic actors' in society but have amalgamated with the technology they use, extending what it means to be human.

Thus, understanding everyday dependencies should be placed at the forefront of future investigations. The Technology Integration Model (TIM) outlines how two components predict technology use: habitual use in response to context and self-regulated use via a cost-benefit decision process. Motivational drives also play a part through influencing the perceived advantages during cost-benefit decision making. In suit, previous work has shown motivations to be an important factor related to Facebook dependency (Ferris & Hollenbaugh, 2018). Thus, if it is conceptually incorrect to apply addiction and problematic use frameworks to everyday use and dependencies, alternative models may provide a theoretical route forward. As technology can both and extend and subtract from a user, TIM provides a more balanced view in regard to the effects of technology use, as it does not assume the impact of use is binary (e.g., is either good or bad). Thus, smartphone use in the 21st century may simply be a component of a normative emotional and physical state. TIM, therefore, has the possibility to re-focus psychological research beyond solely the study of pathological use when investigating the impacts of technology on people and society. This alongside its focus on measuring technology use in an objective manner may encourage the exploration of several new streams of research.

7.3. Practical and Applied Issues

7.3.1. Methodological advancements and limitations

Technological advances during data collection need to occur not only in cognitive and neuroscience fields, but also in social and personality psychology disciplines. Here, there have been fewer advancements in terms of the adoption of new technologically aided methodologies, apart from a switch to online questionnaire methods (Sassenberg & Ditrich, 2019). Perhaps in response, new sub-disciplines in psychology such as Psychoinformatics are exploring how smartphones can be used to collect behavioural data outside the lab, by utilising the many sensors and computer power they contain (Aharony, Pan, Ip, Khayal, & Pentland, 2011; Miller, 2012; Montag, Duke, &

Markowetz, 2016; Montag & Elhai, 2019; Yarkoni, 2012). As chapter one describes, these methods have less reliance on self-reports, have greater ecological validity, and can be used to longitudinally measure a particular behaviour. Consequently, chapters four, five and six study smartphone behaviours 'in situ', outside the lab, and across several days, resulting in detailed and objective observational data. Therefore, the methodologies used within this thesis became more technically challenging as the chapters progressed. However, heightened validity of these methods was found to be critical in chapter six, as measuring smartphone use, via problematic use scales were shown to impact the relationship between smartphone use and mental health in comparison to findings from objective logs. As scales are a dominant method in studies which examine the impact of technology use on society (Boase & Ling, 2013; Ellis, 2019; Thomée, 2018), it is possible that many existing findings could be the product of measurement choice and would change if replicated with greater objectivity. This concern has been previously been raised when discussing if psychology is facing a 'measurement crisis' whereby existing research lacks validity (Flake & Fried, 2019). However, this thesis provides a potential route forward by advocating that smartphone driven methodologies could improve scientific rigour in psychological science.

Chapter four established that no other method could be used as a substitute for objective measures, as neither psychometric scales nor subjective estimates had large enough relationships with actual use. Therefore, whilst smartphone methodologies have their own set of technical challenges, it is worth persevering and exploring ways around these. For example, the Android operating system does not create a 'screen off' signal if a person's smartphone battery totally depletes. This can result in logs which state a particular usage session lasted many hours, in particular if the battery depletes overnight. To control for this, median daily hours of use were calculated in chapters four, five and six to minimise the influence of extreme events. However, software can now log when a person's phone restarts, so any excessive periods of 'screen on' immediately before this 'restart log' can now be removed (Geyer, et al. 2020). Other challenges faced in chapter's four, five and six included subject attrition during continuous logging over weeklong periods. This was occasionally the result of participants losing or breaking their phones but was sometimes caused by the Android operating system 'killing applications' which log data continuously in the background, for the purpose of preserving battery. One way to get around this is to 'white list' a particular application in the phone's settings and was incorporated in the procedure of chapters five and six. However, the variety of devices which run the Android operating system can affect the success of this whitelisting, and therefore logging applications work better on some smartphone brands than others (see dontkillmyapp.com).

Another solution is to not continually track a user, but instead get retrospective data, that is collected and stored by the device as part of the operating system. For example, Android phones have second-by-second logs of a person's past five days of smartphone use, which can be retrieved and emailed to researchers via newly developed applications (Geyer, et al. 2020). iPhones store data to a lower resolution (hourly usage) documenting a person's past usage over the past week and was adopted in chapters four and six. However, unlike Android applications, it is not possible to create an application for Apple iPhones which extracts this usage data without participant effort. In chapter's four and six, participants were required to relay the usage information from their devices, and input this into surveys which could have errors in itself (e.g., mistyping or changing the numbers). Therefore, even objective methods require an assessment of their accuracy to ensure data is collected in a reliable and accurate manner (Boyd, Pasca, & Lanning, 2020). In chapter four, the similarity in the average daily hours of use and pickups between two separate samples of iPhone and Android users provided a validity check that this participant inputting was not largely impacting the quality of data.

It might further be an issue that currently retrospective methods only collect data for six days maximally. Therefore, researchers would need to repeat data collection again if wanting to capture usage for a longer period of time. However, chapter four identified that five days of smartphone data is sufficient enough to be representative of an individual's general smartphone screen time, and only two days is needed for 'pickups' and 'checks' variables. Consequently, for most projects, the data gathered through retrospective logs should be sufficient. However, a final limitation of 'Apple Screen Time' tools is that the processes behind how it measures usage is closed source, meaning that researchers are not privy to the exact mechanisms behind how the logs are made. In this thesis, informal validity checks were performed, whereby the researcher interacted with a smartphone for 30 minutes and timed how long each application was used for on a stopwatch. Then the times derived from the stopwatch were compared to that captured by 'Apple Screen Time'. These checks came back satisfactory, however formal validity studies would increase the credibility of using these method's in future research.

Open source Android applications or development platforms on the other hand outline exactly how the application is measuring usage, down to the signal's it listens to in the

Android operating system. However, often these are not maintained, creating barriers that prevent past platforms/applications from being used in current research. For example, Christensen et al. (2016) developed an application when examining the relationship between objective screen-time and sleep. However, the application used in this project is no longer available for scientific research due to funding limitations. The application required constant maintenance due to an ever-updating Android operating system, which was not possible without further funding. The same issue resided with the application developed in chapter four, which used an open-sourced FunF framework to build Android applications (Aharony et al., 2011). This framework no longer performed well with later Android systems, which was discovered during pilot testing for the study in chapter five. As this worked in chapter four at the beginning of the PhD project, this highlights a problem concerning the speed of these frameworks becoming outdated, requiring constant maintenance by the developers. Consequently, in chapter five and six, data was collected using an application that was created in-house for the purpose of this PhD project. However, for these methods to be used more widely, there needs to be some stability in the resource's researchers can use to build these applications, especially if they do not originate from a computer science background with prior programming knowledge. Software such as PsychoPy3 achieves this goal for laboratory studies (see https://www.psychopy.org), however a similar solution is required for smartphone-based research. In sum, researchers are required to evaluate these limitations when picking the most appropriate way to measure objective usage for the particular project being pursued.

7.3.2. Analytical considerations

The study of digital traces often results in large-scale and noisy data (Yarkoni, 2012). Second-by-second smartphone logs is one example of this, whereby each person has potentially thousands of usage events collected over a week-long period. Thus, even the study of simple digital traces requires several stages of cleaning and processing to get the data to a point whereby statistical tests can be conducted. This cannot be achieved using software such as SPSS. Consequently, as the thesis progressed in chapter's five and six, the analysis included the development of custom R scripts which performed this processing. Therefore, researchers are required to undergo a 'learning curve' if wanting to adopt these methods by studying how to programme analysis scripts in languages such as R, Python or MATLAB.

It is important to note that there are several choices a researcher can make during this cleaning, and some 'degrees of freedom' around how variables are created from these logs. For example, second-by-second logs are infinitely divisible, whereby data processing can create hour-by-hour variables, daily usage variables or analyse specific periods such as evening or morning use. It is possible that researchers can slice up data in several ways until it shows desired or significant effects. Whilst having benefits for exploratory research, it is even more pertinent that analysis methods are preregistered if wanting to conduct hypothesis testing. Chapter six followed suit by preregistering all analysis prior to data collection and was a useful exercise when learning about open science practices. Furthermore, as R is open source, the analysis scripts for chapter's five and six were uploaded alongside data files on the open science framework. Following these practices can heighten transparency and reproducibility in psychological science, as long as people provide data dictionaries and properly comment their code, so it is accessible to others who acquire it (Munafò et al., 2017).

Therefore, as this thesis progressed across the chapters, more open science practices were incorporated into the procedures behind carrying out the research and the dissemination of resources.

Becoming comfortable in the programme language R can also provide new opportunities to utilise computer science methods such as machine learning. In chapters three and five, tree-based classification algorithms were used to predict smartphone operating system ownership and individual users. In particular, tree-based algorithms were highly suited to the task of visualising predictive models due to their flowchart-like output, which can be easily understood by those without specific statistical knowledge (see Fig. 3.4.). Tree-based models are also non-parametric, and have improved accuracy in comparison to traditional regression models when used on data that violates assumptions, and was therefore useful in chapter three when modelling a variable with a skewed distribution (Merkle & Shaffer, 2011). In addition, they can effectively deal with missing values and are minimally impacted by outliers (Iniesta, Stahl, & McGuffin, 2016; Merkle & Shaffer, 2011) Furthermore, traditional regression modelling is restrictive in terms of what interactions can be assessed due to these having to be pre-defined before running the analysis (Venkatasubramaniam et al., 2017). When using decision trees in chapter three, gender and phone as status object were found to interact with one-another when predicting smartphone ownership (see Fig. 3.4.). Thus, tree-based models can discover new interaction effects, and easily model multi-way interactions (King & Resick, 2014). As a result, if data violates common assumptions or is likely to involve an interplay of several variables interacting with one another, this thesis showed that tree-based models are an effective solution for this type of analysis.

Chapter three also tested several hypotheses by adding variables into models one-by-one and then assessed whether this significantly improved models in binary logistic regression analysis, and whether this increased accuracy in decision tree modelling. Therefore, it is possible to conduct hypothesis driven research using machine learning methods (Yarkoni & Westfall, 2017). The ability to test hypothesis is important when confirming a researcher's intuition that a certain digital trace would be informative of a person's individual difference. However, machine learning methods also have the common practice of checking the reliability of a previous model by testing predictions on unseen data (Yarkoni & Westfall, 2017). In chapter three, the classification accuracy of a decision tree when predicting smartphone ownership was 67.29% on test data, which is more likely to generalise to future sample's than predictions made on training data. Consequently, it has been proposed that machine learning algorithms could be incorporated into the analysis of psychological research to help address the replication crisis (Yarkoni & Westfall, 2017).

Thus, it can be considered a limitation in chapter three that the second data set wasn't fed through the final model to assess prediction accuracy. Instead, the beta values of the final model were decomposed so that an algorithm could be programmed in Qualtrics for the purpose of participants getting real-time feedback on their smartphone operating system predictions. Whilst great for public engagement events, future analysis could treat this second round of data-collection as test data. However, chapter five did use the splitting of training and test data to assess the behavioural consistency of daily smartphone checking and application usage behaviours. Notably, unique individuals could be predicted from one day's worth of unseen data, when models were trained on six days of past usage data. Therefore, the adoption of machine learning methods into psychological science has many benefits and would be useful to teach students on both taught and research programmes.

Throughout this thesis, multiple comparisons have often been conducted when assessing hypotheses. One must therefore be mindful of an increased chance of Type 1 errors (false positives), whilst avoiding overly conservative corrections which reduce power and increase the chance of Type 2 errors (false negatives) (Field, Miles, & Field; 2012). For example, if one conducts 20 significance tests, it is highly likely that one will produce a significant result when α is set to .05. Several steps have been taken throughout to mitigate such issues.

In Chapter 3, several models were built when predicting smartphone ownership. In this chapter, Type 1 errors here were controlled for by assessing the reliability of findings across multiple models, and only accepting those which were repeatedly found. In Chapter 4, scores from each psychometric scale were compared to objective smartphone use variables. However, effect sizes, rather than p-values, were used to determine if psychometrics could be an adequate proxy for objective measures, and therefore mitigated some of the issues described above. As part of Chapter 5, several correlations were performed to explore if there were any relationships between smartphone use and personality/demographics. Many correction methods, such as Bonferroni's would have been overly conservative, due to the number of comparisons being made (Field, Miles, & Field; 2012). Alternatively, Pearson correlations with 95 % bias-corrected and accelerated confidence intervals based on 100,000 bootstrapped samples were conducted to control for Type 1 errors. However, as fewer than 5% of the correlations were significant, these were considered potentially erroneous, and were not used to support any hypotheses. Finally, in Chapter 6, several comparisons were made between health outcomes and technology use. Alphas remained uncorrected, as conclusions from study 1 were only accepted if they were verified on a separate sample in study 2.

7.3.3. Ethical considerations

It was assumed in this thesis that basic digital traces, such as smartphone operating system would have less privacy concerns than more detailed traces such as the content of text messages, call logs or websites visited. Consequently, this thesis explored whether simple digital traces would be sensitive enough to reveal information regarding a person's disposition and could be used instead of more invasive measures. However, making inferences in this manner has privacy concerns in itself, that are removed from the actual data that was collected. Simple meta-data can be used to make deductions, such as personality and gender from smartphone operating system used (see chapter three), a particular user from installed applications (Tu et al., 2018) and a person's home location from sparse call logs (Mayer, Mutchler, & Mitchell, 2016). European data protection laws state that 'special category' data, such as those which describe characteristics such as health, ethnicity, or political beliefs, require greater protection when it comes to gaining consent and permissible uses (Wachter, 2019). As personality traits and individual differences can be predicted with relatively accuracy, some have argued that these inferences should be given the same level of protection in GDPR as sensitive data, which is not currently the case (Wachter & Mittelstadt, 2019).

In particular, it has been proposed that people should have the "right to reasonable inferences" that would require data controllers to 1) explain why certain data is an acceptable medium to make that inference, 2) why this inference is needed for the processing purpose and, 3) whether the data and methods used to draw these inferences are reliable and accurate (Wachter & Mittelstadt, 2019). Without this, user privacy, identity, reputation, and autonomy are not protected against inferences made from digital traces. This is particularly important given than even basic meta-data can reveal sensitive characteristics. If used in artificial intelligence to make decisions, such as computer-based assessments when screening job applicants, these inferences regarding protected characteristics (e.g., ethnicity) could instigate discrimination (Wachter & Mittelstadt, 2019). There is also the risk that anonymised data could be reverse engineered and linked back to an individual (Wachter, 2019). Therefore, it is of extreme importance to make sure there is a legal and permissible reason to make these inferences. Furthermore, people should be informed about the inferences being made from their data when consenting to its use, and analysts need to guarantee these inferences are accurate and free of bias. As a rule of thumb, until new legislation is proposed, researchers should treat inferences with the same level of protection as sensitive data.

Ethical considerations are also required during the creation of smartphone applications which measure usage. There is the temptation in computer science to collect as many digital traces as possible, to see if any relate to personality (Chittaranjan, Blom, & Gatica-Perez, 2013). However, collecting more data that is required for a particular purpose creates further ethical issues, therefore the choice of digital traces to be measured should be carefully selected in research. Having frameworks which allow for this customisation during application building can help address this issue (Geyer, et al. 2020). However, ethical review boards could also assess whether appropriate rationale for the specific traces of interest is provided. In addition, it should be assessed whether an application's requested permissions match the data collection exercise. For example, applications built using the AWARE framework ask for permission to access a variety of personal files (including pictures, videos, etc.). In addition, they ask for access to a device's camera, location, calls, and contacts. This is the case even when simply creating an application which just measures screen "on and off" behaviours (Ferreira, Kostakos, & Dey, 2015). It can be argued that researchers should not have access to this information unless explicitly required by the research project, in order to protect user privacy.

Furthermore, applications need to be secure when it comes to protecting data. The FunF in a Box framework (Aharony et al., 2011), which was used in chapter four to collect data has since announced a security issue; *"The current beta release of FunF In a Box has a security vulnerability that could allow a user of your app access to your other users' data."* Thus, when developing an application which stores data using a server or elsewhere online, researchers need to place the same amount of effort into securing the software as they do when curating the functionality of the application. Data should be encrypted, and decryption keys needs to be stored separately from the data itself to avoid causing a breach. In chapters five and six, to evade having to maintain a secure server, the custom-built applications stored the recorded usage logs on the participants' device itself. This meant that only the user had access to their data, and they had full control over whether to delete or share this data with the researcher at the end of the study. Data stored on their device could be viewed at any time by the participant if they wished to see what data was being collected on their behaviours.

This was considered the most ethical way to store usage data during smartphone logging projects and was therefore adopted in chapters five and six.

7.4. The Future of Smartphone Methodologies in Personality and Psychological Research.

The Psychoinformatics approach can be used to conduct data driven research, and the analysis in chapters four and five provide support for this notion. Accordingly, David Funder describes how the future of personality research resides in descriptive research, in a similar way to how the structure of DNA came from exploratory work (Funder, 2009). He posits that without this, hypothesis could be derived prematurely, and describe artificial links (Funder, 2009). Instead, he proposes that if personality is to understand a person as a whole, exploratory work should first understand how person variables (aka individual differences) are interconnected to situational variables and behaviours (Funder, 2009). Specifically, the formula P = f (B, S), represents the personality triad, whereby a *Person* (P) is a function of how they *Behave* (B) in specific *Situations* (S), in line with the interactionalist approach (Funder, 2009). Much work has already been done when it comes to measuring individual attributes (e.g., personality traits), with less effort directed to documenting and building taxonomies of situations and behaviours (Funder, 2001). Thus, the study of personality may have impulsively conducted hypo-deductive research, without the observation of potentially important P, B and S variables and their subsequent links.

The above does not constitute a theory, but instead a framework in which personality research could be conducted. To get a holistic understanding of human nature, one could aim to measure all three components of the triad. Behaviour can act as the starting point, whereby researchers could decide a behaviour of interest, and then explore the person and situational factors which relate to this behaviour. Take for example the task of understanding technology usage behaviours (B). The TIM model outlines two predictors: Habitual use in response to context (S) and self-regulated use via cognitive decision processes (P). In addition, TIM has the advantage of promoting longitudinal research, by describing how a technology is continued to be used or abandoned over time (T). Thus, one could speculate that 'T' could also be a factor added into the personality equation to represent the developmental part of human behaviour.

Additionally, the equation seems incomplete without incorporating findings from genetic and evolutionary perspectives, which describe the biological roots of personality (Funder, 2001). Notably, in the beginnings of personality theory, Gordon Allport described how individual traits are unique to the individual, which exist in a person's neurology and develop over the course of their life to guide and perform adaptive behaviour (Allport, 1962). Twin and parental studies suggest that personality could be in part inherited via genotypes, and studies which use electroencephalogram or electrodermal measures have found links between nervous system activity and traits (Maltby et al., 2010). Thus, future exploratory work could study how biology influences people's characteristics across time and situations.

Finally, since Gordon Allport's conceptualisations of personality, more recent theoretical accounts have been proposed to explain behavioural consistency in both nomothetic and interactionalist perspectives (Fleeson & Jayawickreme, 2015; Mischel et al., 2008). One of these is the CAPS model (Cognitive-Affective Processing System), which describes how the personality system contains several diverse mental representations (Mischel, 2004). Whenever these are activated in response to situations, these lead to the behavioural consistencies found in behaviour profiles of personality, such as those in chapter five (Mischel & Shoda, 1995). Called cognitive affective units (CAUs) these include "*the person's construal and representations of the self, people, situations, enduring goals, expectations-beliefs, and feeling states, as well as memories of people and past events"* (Mischel, 2004, pp 11). This is not dissimilar to humanistic approaches to personality which understand other people phenomenologically, through their experience of reality and their thoughts (Funder, 2001). Thus, exploratory work can start to understand which of these CAU's are more/less important for behavioural predictions in specific situations. Given all of the above, Funder's equation can be modified to represent the five dimensions of personality:

$$\boxed{p = \int \frac{[N * C * S] \rightarrow B}{T}}$$

It can be said that someone's personality (*p*) is the function of how three factors, neurology (*N*), cognitions (*C*) and situations (*S*) interact and instigate behaviour (*B*) over time (*T*). Mobile technology such as smartphones and smartwatches are currently the only technology which has the potential to measure all these factors simultaneously in an exploratory manner. Whilst a seemingly impossible task, neurology can be measured through galvanic skin responses measured via smart watches, or mobile EEG technologies (Miller, 2012). Cognitions can be measured through ecological momentary assessment via self-reports or cognitive experiments ran on person's smartphone (Ellis, 2020). Situations can be measured via tracking geolocation or using Bluetooth to infer crowdedness (Aharony et al., 2011; Geyer, Ellis, & Piwek, 2019). Behaviours can be measured through assessing digital traces, or further through audio recordings of spoken language and through activity monitoring (Cohen, 2019). As smartphones are 'pocket labs', these can be re-assessed over time (Miller, 2012). Consequently, the framework above can be used to anchor future exploratory work, which holistically captures personality through analysing unique behavioural patterns as a consequence of N, C & S. Further, this can be analysed using decision trees which can model interactions in a data driven way. Subsequently, the future of personality research can be an exciting and rich endeavour.

7.5. Conclusions

To conclude, this thesis aimed to explore the potential and limits of predicting individual differences from everyday smartphone behaviours, by shifting the narrative away from solely studying smartphone use with a pathological lens. Theoretically, this is possible through describing how people seamlessly integrate with the technology they own and use. Throughout this process, people leave behind a 'digital fingerprint' which is reminiscent of their characteristics and can uniquely identify them from a crowd. These traces of use do not have to be complex, as meta-data such as the smartphone operating system a person uses can reveal information regarding a user's personality, as long as there is trace-to-trait relevance. Some individual differences can be better predicted from objective smartphone use than others. For example, age and gender can be discerned from smartphone usage logs, whereas mental health variables only had small positive correlations with screen time. However, an important contribution of this thesis resides in its methodological considerations, as self-reports of technology use can impact the relationships with individual differences and cannot be used as a substitute for objective logs. Additionally, rich accounts of second-by-second smartphone behaviours can be used during descriptive work to understand the norms of everyday technology use. This is pertinent as theories detailing problematic smartphone use may be premature given that smartphones are used on average between 3.71 and 4.75 hours a day, without strong links to negative wellbeing. Further, due to the omnipresence of smartphones, their sensors, and their proximity to owners, this provides new opportunities to study 'out of the lab' behaviour. This type of descriptive work can accumulate to a vast understanding of human behaviours, which can only be captured via mobile sensing technologies, without needing to pre-define what may be discovered. This includes longitudinally studying the variability and consistencies in people's behaviour across situations, which may formulate the future of personality-based assessments, as new unforeseen patterns are found. Therefore, incorporating computer science methodologies into psychological research provides an almost limitless number of possibilities for studying people and society.

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Appendices

Chapter 3 Appendices

Appendix A – Adjectives used in study 3.2.

Highest Loading Adjectives from Lee & Ashton (2008) that are positively related to each HEXACO Factor

Extraversion	Conscientiousness	Honesty-Humility	Agreeableness	Emotionality	Openness to experience
Outgoing	Organized	Sincere	Agreeable	Emotional	Philosophical
Social	Thorough	Honest	Calm	Feminine	Insightful
Lively	Hard-working	Trustworthy	Peaceful	Sensitive	Complex
Vibrant	Efficient	Giving	Patient	Sentimental	Deep
Extroverted	Self-disciplined	Kind	Cooperative	Oversensitive	Introspective
Talkative	Careful	Warm-hearted	Mild	Nervous	Articulate
Sociable	Tidy	Humble	Relaxed	Whiny	Inquisitive
Chatty	Proper	Helpful	Tolerant	Fearful	Unconventional
Cheerful	Diligent	Loyal	Forgiving	Melodramatic	Perceptive
Bubbly	Studious	Compassionate	Lenient	Anxious	Analytical
Vocal	Meticulous	Good-hearted	Easygoing	Gullible	Individualistic
Confident	Responsible	Modest	Pleasant	Moody	Intuitive
Happy-go-lucky	Mature	Kind-hearted	Gentle	Nagging	Intellectual
Energetic	Perfectionistic	Big-hearted	Passive	Clingy	Imaginative

Highest Loading Adjectives from Lee & Ashton (2008) that are negatively related to each HEXACO Factor

Extraversion	Conscientiousness	Honesty-Humility	Agreeableness	Emotionality	Openness to experience
Dull	Irresponsible	Conceited	Quick-tempered	Masculine	Simple
Withdrawn	Careless	Self-centered	Hot-tempered	Fearless	Conservative
Quiet	Disorganized	Snobbish	Short-tempered	Unemotional	Conventional
Antisocial	Reckless	Egotistical	Aggressive	Rugged	Narrow-minded
Shy	Sloppy	Superficial	Blunt	Tough	Bigoted
Gloomy	Messy	Greedy	Argumentative	Heartless	Closed-minded
Introverted	Untidy	Dishonest	Bull-headed	Rough	
Reserved	Inefficient	Condescending	Stubborn	Self-assured	
Negative	Lazy	Arrogant	Forceful	Cold-hearted	
Timid	Absent-minded	Deceitful	Demanding	Unfeeling	
Pessimistic	Immature	Selfish	Temperamental	Insensitive	
Distant	Irrational	Vain	Bossy	Decisive	
Inhibited	Underdisciplined	Untrustworthy	Headstrong	Ruthless	
Unfriendly	Rebellious	Egocentric	Dominant	Unsympathetic	